Exhibit A

EXPERT REPORT OF PETER S. ARCIDIACONO

Students for Fair Admissions, Inc. v. University of North Carolina
No. 14-cv-954 (M.D.N.C.)

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1. Executive Summary

I am a Professor of Economics at Duke University. My area of academic expertise is labor economics; I have published numerous peer-reviewed articles on issues of race/ethnicity and admissions decisions in higher education. I was retained by Students for Fair Admissions, Inc., in this case to review and analyze the data and information produced by the University of North Carolina-Chapel Hill ("UNC") and to answer several questions about UNC's admissions process, using accepted econometric and statistical methods and techniques that I have used in my published academic work for the past fourteen years:

- What role does an applicant's race/ethnicity play in admissions decisions made by UNC?
- Is race a predominant factor in UNC's admissions process?
- Can any other aspects of the admissions process explain the observed effect of race?

To answer these questions, I reviewed data from the admissions cycles covering the classes of 2016 to 2021,[1] including data on in-state and out-of-state applicants. North Carolina has a policy that penalizes UNC for enrolling less than 82 percent of its class from in state, admissions is more competitive for out-of-state applicants. I thus analyze the two groups separately.

Using techniques that are standard in the field of economics, I

[1] Data were received for the 2017 cycle on June 16, 2017. Some students may have been admitted off the waitlist after that date.

constructed a model of UNC's admissions decisions. The model includes a battery of controls that ensures the effect of any applicant characteristic can be accounted for—including test scores, grades, UNC's rating of the files along five dimensions (program, performance, extracurricular, essay, and personal qualities), gender, and race, among others.

My analysis reveals substantial differences across races/ethnicities in academic preparation both in the in-state and out-of-state datasets, particularly when comparing UNC's data regarding African-American and Hispanic applicants (which UNC considers to be underrepresented minorities, or URMs)[2] and Asian-American and white (non-URM) applicants. The non-URMs have significantly higher test scores[3] and high school grades than URMs. Non-URMs also generally receive higher ratings from the UNC admissions officers in academic performance, academic program, extracurricular activities, and essays.[4]

Employing statistical and econometric methods of analysis, it is my opinion, to a reasonable degree of certainty, that:

- Significant preferences are given to in-state URM applicants over

[2] Throughout my report I refer to African Americans and Hispanics as under-represented minorities (URMs) and Asian Americans and whites as non-URMs. UNC also counts Native Americans as URMs, but I do not discuss these results as Native Americans make up less than 2% of the applicant pool.

[3] Indeed, in both the in-state and out-of-state datasets Asian-American and white rejects have, on average, higher SAT math scores than African-American admits.

[4] The one exception is that non-URMs score higher on the personal quality measure assigned by UNC. My analysis indicates that this is a result of racial preferences in the rankings themselves, as I discuss later in the report.

their non-URM counterparts. For example, the overall admit rate for non-URM in-state applicants over this period was 52%. Non-URM applicants would see an average increase in their probability of admission of over 10 percentage points if they were treated as Hispanic applicants and over 16 percentage points if they were treated as African-American applicants.

- Racial/ethnic preferences are even larger for out-of-state URMs. Out-of-state non-URM applicants have an admit rate of 12% over this period. Out-of-state non-URM applicants would see their admission rates more than double (rising by 20 percentage points) if they were treated as Hispanic applicants. And if they were treated as African-American applicants, their admit rates would on average increase over *four-fold*, rising by 42 percentage points.

- Although UNC also gives preferences to first-generation college ("FGC") students, these are much smaller than the racial/ethnic preferences for URMs. Further, UNC gives first-generation URM applicants a much smaller preference for their FGC status than it gives first-generation non-URM applicants. Relative to the non-URM applicant, then, the overall preference the URM applicant receives would be larger if the two applicants were non-FGC than if they were FGC.

This analysis actually understates the effect of UNC's use of race, because the magnitude of the effects depends on how strong the applicant is. Racial preferences have little effect on those whose applications are extremely uncompetitive. To put the magnitude of racial preferences into perspective, consider a male, non-FGC Asian-American applicant whose observed characteristics would imply a 25% chance of admission:

- If he was an in-state applicant, his probability of admission would increase to over 63% (i.e., more than double) had he been treated like an in-state Hispanic applicant, and to over 88% (more than triple) had he been treated like an in-state African American applicant across the full sample period.

- If he was an out-of-state applicant, his probability of admission would increase to over 85% had he been treated like an out-of-state Hispanic applicant and over 99% had he been treated like an out-of-

state African-American applicant across the full sample period.[5] Simply changing this hypothetical Asian-American applicant's race to either Hispanic or African-American would transform him from an unlikely admit to an almost certain admit.

Holding fixed the number of admission slots and removing racial preferences would significantly change Asian-American and white representation at UNC. Fixing the number in-state admits at the levels observed in the data and removing racial preferences would result in 1,219 additional non-URM admits over the six-year period, a 5.5% increase. Fixing the number of out-of-state admits at the levels observed in the data and removing racial preferences would result in 2,482 more non-URM admits from that pool, a 25.7% increase.

Although these numbers indicate that race plays a large role in the admissions process, they likely understate the effect of racial preferences, for at least two reasons:

1. Non-URM applicants are strong on the measures that are observed in the data, suggesting that they would likely be strong on unobserved variables not in the data (e.g., number and scores on AP exams). The general patterns show that as controls are added, racial preferences for URMs increase, suggesting that adding further controls would reveal even larger racial preferences.

2. There is evidence of bias in the personal quality measure that UNC assigns to applicants in favor of African Americans and Hispanics. Removing this bias would lead to even larger gains for non-URMs.

In addition to racial/ethnic preferences, UNC gives preferential

[5] Suppose instead that this hypothetical Asian-American applicant's chances of admission were 10%. His probability of admission would rise to 97% if he were treated as an African-American applicant.

treatment to legacies.[6] The estimated models allow for a comparison of the preferences given to legacies versus preferences for particular races and ethnicities. The estimated preference for in-state legacies is about one-tenth of the preference for African Americans. Preferences for out-of-state legacies are much larger; the estimated magnitude falls in between the preferences given to Hispanics and African Americans.

Despite the large preference for legacies, removing legacy preferences has little effect on the racial/ethnic composition of the admitted class, driven in large part by the fact that only 3.3% of out-of-state applicants are legacies.[7] Indeed, statistical analysis reveals that the number of URMs admitted to UNC is minimally affected by legacy preferences. Racial preferences dominate legacy preferences in terms of the effects on the racial/ethnic composition of the admitted class.

2. Background, Data, and Methods

2.1. Background

I earned a bachelor's degree in Economics from Willamette University, and I earned a Ph.D. in Economics from the University of Wisconsin, where I was awarded a Sloan Dissertation Fellowship. I am a Professor in the Department of

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[6] Preferences for recruited athletes are substantial, with recruited athletes having an admit rate of over 97% over the sample period. Athletes, however, represent only 1.7% of non-foreign admits over this period. For the four major racial/ethnic groups, African Americans have the greatest share of athletic applications and admits followed by whites, Hispanics, and Asian Americans.

[7] The highest legacy share was for whites, followed by African Americans, Asian Americans, and Hispanics.

Economics at Duke University. I joined the Duke Economics faculty as an Assistant Professor in 1999, was promoted to Associate Professor (with tenure) in 2006, and became a Full Professor in 2010. I have taken multiple Ph.D.-level courses in econometrics and regularly teach a Ph.D.-level class on the estimation of dynamic models. My primary fields of interest are Labor Economics, Applied Econometrics, and Applied Microeconomics. These fields all involve the quantitative analysis of economic data through the application of mathematics and statistical methods in order to draw reliable inferences that give empirical content to economic relations.

I have served as an editor or associate editor for several economics journals, including serving as editor for the Journal of Labor Economics, the top field journal in labor economics; a coeditor at Economic Inquiry and Quantitative Economics; an associate editor for the Journal of Applied Econometrics; and a foreign editor for The Review of Economic Studies, one of the top five general-interest journals in economics, and one of the two top-five economics journals that publishes pieces on econometrics.

I have published dozens of works in peer-reviewed academic and economics journals, and have given presentations across the country and around the world on topics in applied economics and econometrics. I also have two survey papers on racial preferences in higher education, including one in the Journal of Economic Literature, widely regarded as the top journal for works synthesizing the literature on a particular topic.

In connection with my work and my research in economics and econometrics, I regularly employ statistical methods and conduct statistical analyses in accordance with generally accepted practices in my field. I have applied discrete choice analysis, where the dependent variable is binary, in much of my work, including using it to characterize the role of race in both undergraduate and law school admissions. I have been awarded numerous grants for research in these areas generally and in particular with regard to the nature, impacts, and the role of race as a factor in admissions decisions in American higher education. A complete copy of my CV, including all published works for the past ten years, is attached in Appendix B.

I was retained in this matter by counsel for SFFA to provide economic and statistical analysis of UNC's use of race as a factor in undergraduate admissions decisions. The rate for my services in this matter is $450/hour, and is not dependent on reaching any particular result or conclusion. As part of this effort, I have been assisted at various points by three colleagues who worked under my direct supervision.

In the past four years, I testified as an expert at a deposition and trial in the case of *Sander v. State Bar of California*, San Francisco City and County Super. Court CPF-08-508880.

2.2. Data

2.2.1. Data Sources

The primary data I used cover the admissions cycles from 2012 to 2017

(that is, for the incoming freshman classes that would make up the graduating classes of 2016 to 2021). These data provide a substantial amount of information on each applicant during this period of time, including data on admissions and enrollment decisions, whether the applicant applied for early decision, academic background measures such as test scores and grades, the five scores that UNC's admissions officers assign to each file, and other demographic measures such as residency status, race/ethnicity, gender, and whether the applicant is a first-generation college student. The data also include information relating to several other special recruiting categories such as scholarship finalists and athletes. Two additional admissions cycles (2010 and 2011) provide data on admissions and enrollment decisions, demographic variables, and test scores, but do not have data on UNC's rankings of the applicants. The data include information on 65,123 in-state applicants and 135,289 out-of-state applicants for the 2012 to 2017 admissions cycles.

Other data were made available to me. Data from the North Carolina Education Research Data Center (NCERDC) provide additional information at the student, teacher, and school levels. The NCERDC data are available for approximately two-thirds of in-state applicants for academic cycles 2016 to 2019 only, and are not available for nearly all out-of-state applicants. Census block group data are available for nearly all in-state applicants for academic cycles 2016 to 2020. Information about the applicant's county and

census tract can be obtained from this census block group data.

In order to isolate the impact of race/ethnicity on admissions decisions, a number of observations are removed from the analysis. Tables A.2.1 and A.2.2 document how the data were modified. First, I dropped all of those who had incomplete applications. These individuals were all rejected. Second, I removed those in special recruiting categories where (i) the admit rate was above 97% and (ii) the observations were somewhat evenly distributed across years were removed. The Appendix provides details of which recruiting categories were removed. I also removed foreign applications, as this lawsuit is concerned with discrimination against domestic applicants and UNC generally treats international applicants as a distinct category, not included in its analysis of domestic applicants and their racial/ethnic identity. I also removed applicants who scored a zero on any of the ratings categories because it is unclear how to interpret those ratings.[8] These refinements reduced the size of the six-year dataset to 57,225 in-state applicants and 105,632 out-of-state applicants.

2.2.2. Scoring & Selection of Applications by UNC

I reviewed numerous depositions and documents produced by UNC in this case to understand the admissions process. A complete list of documents I reviewed is set forth in Appendix C. Based on that review, I provide the

[8] This removed less than half a percent of all applicants.

following overview of UNC's admissions process:[9]

UNC has two admissions cycles: early action and regular action. For the early action cycle, applications are due in October with decisions coming in late January. For regular action, applications are due mid-January with decisions coming in late March. UNC's process for reviewing applications is the same for each cycle. UNC also has two applicant pools: in-state and out-of-state. North Carolina policy penalizes UNC when out-of-state students exceed 18% of its undergraduate population.[10] Because there are substantially fewer slots for out-of-state students than their in-state counterparts and around twice as many applicants, admission to UNC through the out-of-state pool is much more competitive.

Applicants submit a variety of application materials to UNC either directly or through the Common Application. All applicants are expected to submit standardized test scores, high school transcripts, information about extracurricular activities, and any other achievements the applicant wants UNC to consider. Applicants also submit an essay and letters of recommendation.

All applications are randomly assigned to and read by at least one person in the admissions office. When the first reader reviews the application, the reader calculates the applicant's GPA and ranking in class, if that information is available. More importantly, that reader also scores the applicant in five

[9] This overview is derived largely from the deposition testimony of Steve Farmer, Barbara Polk, Jennifer Kretchmar, Jared Rosenberg, and Ni-Eric Perkins, as well as my review of the data and other documents referenced in Appendix C.

[10] UNC Board of Governors Policy 700.1.3 (adopted March 14, 1986).

categories: (1) program; (2) performance; (3) extracurricular; (4) essay; and (5) personal qualities.

For program, the reader calculates the difficulty of the student's curriculum on a scale from 1 to 10.[11] It is based on the total number of AP, IB, and dual enrollment courses that a student has taken. If the student has taken between 1 and 3 of those courses, the student receives a 3. The student receives an additional point to that score for each additional course taken up to a score of 10; at that point, additional advanced classes do not impact the program score.

The reader rates the student's academic performance and extracurricular record on a scale from 1 to 10, with higher numbers associated with stronger students on those dimensions.[12] For performance, a student with all As receives a 10, a student with half As and half Bs receives a 5, 6, or 7 depending on whether the student's grades were falling or improving over time.[13] For extracurricular, the reader considers anything that is not part of the designated academic curriculum with a grade and focuses on the quality of the student's activities, rather than the quantity.[14]

The reader rates the essays and personal qualities on a 1, 3, 5, 7, and 10 scale. For essays, UNC has a grading rubric[15] to evaluate strength in writing,

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[11] Rosenberg Depo. 243:17

[12] Rosenberg Depo. 144:22-145:12

[13] Rosenberg Depo. 236:13-21, 245:5-13.

[14] Rosenberg Depo. 246:5-247:15

[15] UNC instituted this rubric in 2015. *See* Rosenberg Depo. 200:3-8; UNC0064255.

organization, vocabulary, grammar, voice, and sentence structure. For personal quality, the reader evaluates factors such as the student's achievements, impact in school or community, whether the student has overcome adversity, and other similar, unique facts about the student.[16] The content of the essay, rather than the quality of its writing, may be considered in this personal rating. And race can be considered for this rating though readers are not specifically trained to do so.[17]

Once those five scores are calculated, the reader then considers the entire application to make a recommendation regarding admission. In addition to those five scores, the reader considers all information from the application, including the applicant's standardized test scores and the recommendation letters. The reader then makes a preliminary decision whether to admit, deny, defer (during early action), or waitlist (during regular action) the applicant.[18] UNC has acknowledged that race can be the "tipping point" in whether a particular applicant is granted admission.[19]

Whether an application receives a second read depends on context. For the in-state pool, if the first reader recommends to admit or deny, then the application does not receive a second reader unless the reader specifically requests one. But if the first reader recommends the waitlist, however, that application will receive a second read. For the out-of-state pool, if the first reader

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[16] Rosenberg Depo. 249:10-250:1.

[17] Rosenberg Depo. 250:13-251:5; Perkins Depo. 40:3-43:10.

[18] Perkins Depo. 44:13-46:25; Rosenberg Depo. 148:10-149:20.

[19] Polk Depo. 42:7-15.

recommends to admit or waitlist, then the application requires a second read because of the limited number of slots for out-of-state. Likewise, because the pool is so competitive, an initial recommendation to deny does not require a second read.[20]

If an applicant receives a second read, then that reader reviews the application in the same way as the first reader, though the second reader is aware of the first reader's scoring and recommended decision.[21] After finishing review, the second reader enters the preliminary decision and that application moves on to the School Group Review ("SGR") phase.[22]

SGR takes place over about three weeks for both admissions periods. UNC has stated that the SGR process has two primary goals.[23] First, it allows the admissions office to consider its expected enrollment for the incoming class and then, as part of trying to avoid over- or under-enrollment, adjust the total number of applicants who receive an offer of admission. Second, it serves as a quality control measure that allows senior members of the admissions office to review the readers' provisional admissions decisions to ensure that decisions for applicants from the same high school are reasonable in context.[24]

To that end, the SGR process does not involve the entire admissions staff;

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[20] Rosenberg Depo. 122:10-123:4,148:10-149:20.

[21] Rosenberg Depo. 135:18-21, 144:21-145:20.

[22] Rosenberg Depo. 149:9-20, 177:22-179:3.

[23] UNC0079438 (Rosenberg Ex. 8).

[24] UNC0079438 (Rosenberg Ex. 8); Rosenberg Depo. 178:11-181:24.

generally, only senior staff and experienced readers conduct that process. During the review, each high school's applicants are initially sorted by GPA, with the applicants' preliminary admissions decisions listed. The SGR reviewer evaluates each applicant's status in comparison with other students from that same high school. The reviewer can then change an applicant's status if the reviewer disagrees with the recommended decision. The applicant's race is available to the SGR reviewer during the decision-making process even though UNC recently removed it from the SGR reports themselves. Once the SGR decisions are finalized, UNC releases its admissions decisions to the applicants.[25]

In addition to these procedures, UNC compares the preliminary makeup of the current class to the preliminary makeup of the previous year's class at the same point in time in that prior year's process. Until this lawsuit was filed in November 2014, the admissions office made available to its staff the racial makeup of the current class as compared to the racial makeup of the previous year's class as the process moved forward. That information was also discussed at meetings of the entire admissions staff, including those who were involved in the admissions reading process. Around the time this lawsuit was filed, UNC changed its policy and only Steve Farmer and Barbara Polk have access to that information after the early action period is completed.[26]

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[25] Rosenberg Depo. 182:1-187:10; Polk Depo. 31:5-13, 56:8-57:19, 128:15-131:7.

[26] Polk Depo. 32:9-34:18, 42:16-46:21

2.3. Methodology

2.3.1. Measuring the Role of Race in the Selection of Applicants for Admission

Examining how decisions are made with regard to who is admitted to a college, who is hired for a job, or whether to attend a college are complicated processes depending on many factors. Some of the factors that affect these decisions will be readily observed, while other factors may be difficult to quantify or not in the data. Yet despite these processes being complicated, it is still possible to utilize the data to understand how decisions are made through statistical and econometric methods. Indeed, much of empirical economics does exactly this.

So although UNC purports to use a "holistic" admissions process, one can still quantify the role various factors play in the admissions decisions. Those who are admitted have different characteristics than those who are rejected, which has implications for how these characteristics affect the admissions decision.

To evaluate the magnitude of racial preferences for URMs in admissions, I use generally accepted methods for analyzing outcome variables that can take on only one of two values. Here the outcome measure is whether or not a particular applicant is admitted. A standard way of estimating a model with a binary outcome is to use a logit model. The mathematical basis for the model is described in Appendix D.

By making an admission decision, UNC reveals an implicit ranking of the applicants: those who are admitted were ranked higher than those who were not

admitted. This ranking depends on characteristics that are seen in the data and other factors that are not. By estimating a model of how UNC makes their admission decisions, I can calculate an applicant's probability of admission given their observed characteristics. This probability reflects how often the applicant would be admitted if this applicant was seen multiple times, each with a different value of their unobserved characteristics.[27]

One of the observed characteristics included in the model is the race of the applicant. The relationship between this variable and the admission decision depends on what controls are included in the model. By controls, I mean factors that may affect the admissions decision but also may vary by race. For example, suppose group A has the same admit rate as group B, but group A has higher test scores than group B. Assuming that higher test scores make admission more likely, excluding test scores would make it appear as though being a member of group A or B did not matter for admission. By controlling for test scores, one can show that group A was being held to a higher standard than group B, all else equal.

One of the key advantages of the UNC database is that the set of observed characteristics is more robust than what is typically available. Many peer-reviewed studies in excellent journals have been published analyzing discrimination with data of much lower quality. But there is nonetheless the issue, which is faced by all discrimination studies using observational data, of

[27] In fact, UNC has developed and used similar models for its own purposes. *See, e.g.,* UNC0090652.

whether accounting for unobserved characteristics would lower the estimated magnitude of racial preferences.

For example, consider differences in earnings across college majors. A large gap exists, with those in engineering and business typically earning more than those who majored in humanities and education. However, when controls for test scores and hours worked are included, the gap shrinks. A remaining question, then, is whether additional controls would lead to a further shrinking of the gap or would eliminate the gap altogether. The assumption operating in the background is that if one group is stronger on the observed measures, it is reasonable to believe that the same group is also stronger on the unobserved measures. If, however, including additional characteristics leads to a widening of the gap between the two groups, then it is reasonable to expect that if more controls were added, the gap would, if anything, increase.

2.3.2.Measuring the Role of Race in the Scoring of Applicants

Importantly, the observed applicant characteristics themselves may be the result of racial penalties and preferences. For example, suppose URMs also receive preferences for race in connection with one of UNC's component ratings. Controlling for a measure that already incorporates a preference would result in under-estimating the magnitude of preferences URMs receive.

To assess whether there are racial preferences in the rating themselves, I use a similar approach to that used in detecting racial preferences in the selection of applicants for admission, except that now the rating itself is the

dependent variable. Here, I have more information because UNC's ratings are not simply zero or one but take on a number of discrete values (e.g. 3, 5, 7). These discrete values again show UNC's implicit ratings of the applicants on various measures. A standard technique for modeling ordinal ratings is an ordered logit. An ordered logit is based on the premise that with access to all of the observed and unobserved characteristics I would be able to match UNC's rating. This rating would result in cutoffs where those above a certain cutoff would receive a 10, then those above the next cutoff would receive a 9, etc.

Further, I can see how adding controls affect the coefficients on race/ethnicity. To the extent that significant differences across races/ethnicities remain after controlling for observed characteristics, I can see whether the remaining differences are consistent with the patterns expected from the observed characteristics. For example, if non-URM applicants have characteristics that would suggest they should receive higher ratings than URMs, but they receive lower ratings, this would be evidence of racial preferences in the ratings themselves.

2.4. Admission Rates

I first consider admission rates by race/ethnicity and whether the applicant is in-state or out-of-state. These are reported in Table 2.1. The first three columns show the following:

(i) the admit rate for in-state applicants of a particular race/ethnicity,

(ii) the share of in-state applicants that are a particular race/ethnicity, and

(iii) the share of in-state admits that are of a particular race/ethnicity.

The next three columns repeat the analysis but this time for out-of-state applicants. The final three columns pool the two groups.

Table **2.1**: Admission Rates, Applicant Shares and Admit Share (%) by Race and Applicant Type

	In-State			Out-of-State			Overall		
	Admit Rate	Appl. Share	Admit Share	Admit Rate	Appl. Share	Admit Share	Admit Rate	Appl. Share	Admit Share
White	50.86	64.82	68.80	10.91	60.35	48.69	25.60	61.92	61.91
African American	30.53	13.59	8.66	16.74	9.07	11.24	22.92	10.66	9.54
Hispanic	40.96	6.27	5.36	20.18	8.54	12.75	26.09	7.74	7.89
Asian American	53.56	10.51	11.75	16.60	15.39	18.89	26.59	13.67	14.20
Native American	48.10	1.43	1.43	29.79	0.90	1.98	38.26	1.09	1.62
Hawaiian	47.06	0.12	0.12	9.22	0.13	0.09	21.53	0.13	0.11
Missing	57.10	3.26	3.88	15.28	5.62	6.35	25.28	4.79	4.73
Total	47.92	57,225	27,422	13.52	105,632	14,281	25.61	162,857	41,703

Notes: The row labelled "Total" denotes the overall admit rate for the admit rate column and sample sizes for the applicant share and admit share columns
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

The difference between the overall admit rates for in-state and out-of-state applicants is striking. The overall admit rate for out-of-state applicants is 13.5%, while for in-state applicants it is 47.9%. Practically speaking, then, UNC's admissions process operates almost like two different schools. For out-of-state applicants, UNC is a highly selective school; for in-state applicants, UNC is moderately selective.

In-state non-URM applicants (i.e., Asian Americans and whites) have significantly higher admit rates than their African-American and Hispanic

counterparts. But out-of-state URM applicants have much higher admit rates that out-of-state non-URM applicants. In particular, Hispanic applicants have the highest out-of-state admit rate for all racial/ethnic groups; and the admission rate for out-of-state African-American applicants is five percentage points higher than for out-of-state white applicants. As a result, although the in-state share of applicants who are African American is larger than the corresponding out-of-state share, the share of out-of-state admits who are African American is two percentage points higher than the corresponding in-state share.

Table 2.2 reports the results by class year. In every year, African-American and Hispanic admit shares are below their application shares in the in-state data and above their application shares in the out-of-state data. For white applicants, the reverse is true.

The data reported in Tables 2.1 and 2.2 show the overall admission rates and therefore do not account for differences in preparation across racial/ethnic groups. The rest of this report is designed to explain the role of race/ethnicity in admissions after accounting for differences in preparation.

2.5. Summary Statistics

Table 2.3 presents summary statistics of our overall sample, by admissions status and by applicant race for the main race categories. Table 2.4 repeats the analysis for out-of-state applicants.

Table 2.2: Admission Rates, Applicant Shares and Admit Share (%) by Race, Applicant Type, and Class Year

	In-State			Out-of-State			Overall		
	Admit Rate	Appl. Share	Admit Share	Admit Rate	Appl. Share	Admit Share	Admit Rate	Appl. Share	Admit Share
2016									
White	50.55	68.39	71.81	9.77	65.71	53.03	24.81	66.67	66.00
African American	32.65	13.43	9.10	16.96	9.43	13.22	23.93	10.87	10.38
Hispanic	39.92	5.63	4.66	21.63	7.19	12.85	27.20	6.63	7.19
Asian American	54.59	9.73	11.03	13.75	13.69	15.55	25.39	12.27	12.43
Native American	48.41	1.44	1.45	33.53	1.09	3.03	39.86	1.22	1.94
Hawaiian	40.00	0.11	0.10	17.65	0.11	0.16	25.93	0.11	0.11
Missing	70.91	1.26	1.85	9.49	2.78	2.18	21.96	2.23	1.95
2017									
White	52.54	64.94	68.80	10.31	60.06	50.90	25.78	61.76	63.17
African American	30.37	13.97	8.55	14.88	9.27	11.33	21.79	10.91	9.42
Hispanic	47.49	5.43	5.20	17.36	8.36	11.93	25.12	7.34	7.32
Asian American	55.70	9.56	10.74	14.70	13.34	16.12	26.06	12.03	12.44
Native American	48.15	1.53	1.49	22.75	1.01	1.90	34.11	1.20	1.62
Hawaiian	80.00	0.11	0.18	18.75	0.10	0.15	42.31	0.10	0.17
Missing	56.27	4.45	5.04	11.90	7.86	7.68	22.20	6.67	5.87
2018									
White	54.92	65.42	69.27	12.25	61.98	49.11	27.46	63.16	61.97
African American	34.38	13.51	8.95	21.89	8.96	12.68	27.41	10.53	10.30
Hispanic	47.61	6.00	5.50	21.92	8.51	12.06	28.86	7.64	7.88
Asian American	54.72	11.42	12.05	18.60	15.47	18.60	28.69	14.07	14.42
Native American	56.78	1.35	1.48	39.75	0.97	2.49	46.95	1.10	1.85
Hawaiian	42.86	0.08	0.07	6.67	0.18	0.08	13.51	0.15	0.07
Missing	62.37	2.22	2.67	19.57	3.94	4.98	29.36	3.35	3.51
2019									
White	52.59	64.55	69.25	14.01	59.43	47.72	28.21	61.22	60.66
African American	31.06	13.40	8.49	20.41	8.94	10.46	25.16	10.50	9.28
Hispanic	43.09	6.21	5.46	25.68	8.41	12.38	30.62	7.65	8.22
Asian American	50.31	10.80	11.08	21.90	15.90	19.97	29.49	14.12	14.63
Native American	54.81	1.51	1.68	37.07	0.69	1.48	46.61	0.98	1.60
Hawaiian	63.64	0.12	0.16	4.17	0.14	0.03	22.86	0.14	0.11
Missing	55.56	3.41	3.87	21.44	6.48	7.96	28.96	5.41	5.50
2020									
White	49.71	63.80	67.37	11.16	58.37	48.20	25.76	60.31	60.85
African American	30.66	13.41	8.74	14.13	8.58	8.98	21.83	10.31	8.82
Hispanic	38.27	6.54	5.32	19.74	9.18	13.40	25.01	8.23	8.07
Asian American	53.84	10.74	12.28	15.91	16.29	19.18	26.10	14.30	14.63
Native American	43.66	1.36	1.26	28.78	0.74	1.58	36.30	0.96	1.37
Hawaiian	12.50	0.15	0.04	4.00	0.13	0.04	7.32	0.14	0.04
Missing	58.75	4.00	4.99	17.37	6.71	8.62	27.69	5.74	6.22
2021									
White	46.28	62.71	66.83	8.52	57.86	44.68	22.40	59.55	59.71
African American	25.80	13.78	8.18	13.54	9.28	11.39	18.97	10.85	9.21
Hispanic	34.66	7.41	5.91	16.58	9.23	13.87	22.02	8.59	8.47
Asian American	52.78	10.73	13.04	14.72	16.92	22.57	24.38	14.76	16.11
Native American	39.75	1.39	1.27	20.81	0.91	1.72	29.33	1.08	1.42
Hawaiian	57.14	0.12	0.16	10.34	0.13	0.13	25.58	0.13	0.15
Missing	51.79	3.86	4.60	10.98	5.66	5.63	21.91	5.03	4.93

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table 2.3: Application Summary Statistics by Race: In-State Applicants

	White			African American			Hispanic			Asian American			Total		
	Reject	Admit	Total	Reject	Admit	Total	Reject	Admit	Total	Reject	Admit	Total	Reject	Admit	Total
Admitted	0.00	100.00	50.86	0.00	100.00	30.53	0.00	100.00	40.96	0.00	100.00	53.56	0.00	100.00	47.92
Female	56.93	60.67	58.83	65.91	70.09	67.19	62.25	61.22	61.83	55.83	56.97	56.44	58.87	61.10	59.94
First-generation college	18.25	13.21	15.69	41.68	33.57	39.20	51.06	40.48	46.73	30.03	20.04	24.68	26.06	17.27	21.85
Legacy	17.42	21.84	19.67	6.35	9.27	7.24	4.53	4.90	4.68	4.62	5.77	5.24	13.09	17.76	15.33
Waiver	6.92	5.06	5.97	45.86	37.99	43.46	36.01	28.91	33.10	16.26	12.19	14.08	17.34	10.27	13.95
Missing SAT or ACT	0.29	0.00	0.14	0.59	0.00	0.41	0.71	0.07	0.45	0.36	0.00	0.17	0.38	0.00	0.20
Missing class percentile	14.53	16.20	15.38	7.42	13.14	9.17	9.91	13.81	11.51	9.09	18.18	13.96	12.45	16.40	14.34
Missing GPA	0.03	0.04	0.04	0.02	0.04	0.03	0.03	0.04	0.03	0.03	0.06	0.04	0.03	0.04	0.04
SAT math (z-score)	-0.69	0.06	-0.31	-1.57	-0.73	-1.31	-1.17	-0.37	-0.84	-0.46	0.47	0.04	-0.87	0.02	-0.44
	(0.75)	(0.66)	(0.80)	(0.82)	0.69	(0.87)	(0.83)	(0.73)	(0.88)	(0.92)	(0.73)	(0.95)	(0.87)	(0.74)	(0.93)
SAT verbal (z-score)	-0.55	0.25	-0.14	-1.42	-0.51	-1.14	-1.03	-0.16	-0.68	-0.74	0.27	-0.20	-0.77	0.17	-0.32
	(0.83)	(0.73)	(0.88)	(0.88)	0.81	(0.96)	(0.93)	(0.83)	(0.99)	(0.96)	(0.84)	(1.03)	(0.93)	(0.80)	(0.98)
High school class percentile (0-100)	79.10	93.58	86.34	74.20	91.56	79.26	74.87	91.81	81.57	74.86	92.78	83.94	77.28	93.14	84.64
	(14.21)	(6.17)	(13.13)	(17.51)	(7.80)	(17.24)	(16.54)	(7.46)	(16.00)	(16.26)	(6.96)	(15.33)	(15.48)	(6.63)	(14.54)
GPA (z-score)	-0.09	0.90	0.41	-0.67	0.59	-0.28	-0.39	0.74	0.07	-0.14	1.03	0.49	-0.23	0.87	0.30
	(0.78)	(0.60)	(0.85)	(0.90)	(0.57)	(1.00)	(0.82)	(0.58)	(0.92)	(0.82)	(0.59)	(0.92)	(0.84)	(0.61)	(0.92)
Program Rating (1-10)	5.35	7.52	6.45	4.94	7.30	5.66	5.34	7.42	6.19	6.35	8.56	7.53	5.37	7.62	6.45
	(2.32)	(2.00)	(2.42)	(2.62)	(2.31)	(2.75)	(2.56)	(2.18)	(2.62)	(2.58)	(1.76)	(2.44)	(2.45)	(2.05)	(2.53)
Performance Rating (1-10)	5.62	8.37	7.02	4.55	7.40	5.42	4.93	7.77	6.09	4.96	8.03	6.60	5.29	8.20	6.69
	(1.89)	(1.41)	(2.16)	(1.82)	(1.60)	(2.19)	(1.85)	(1.51)	(2.22)	(1.89)	(1.52)	(2.29)	(1.92)	(1.48)	(2.26)
Extracurricular Rating (1-10)	5.42	6.07	5.75	4.90	5.69	5.15	5.00	5.71	5.29	5.09	6.02	5.59	5.26	6.01	5.62
	(1.20)	(1.03)	(1.16)	(1.39)	(1.10)	(1.36)	(1.37)	(1.17)	(1.34)	(1.35)	(1.14)	(1.33)	(1.28)	(1.07)	(1.24)
Essay Rating > 5	0.05	0.15	0.10	0.03	0.13	0.06	0.04	0.14	0.08	0.05	0.19	0.13	0.05	0.16	0.10
Personal Quality Rating > 5	0.11	0.24	0.18	0.14	0.32	0.20	0.17	0.32	0.23	0.11	0.27	0.20	0.12	0.26	0.19
N	18,229	18,865	37,094	5,401	2,374	7,775	2,119	1,470	3,589	2,794	3,223	6,017	29,803	27,422	57,225

Note: Essay and Personal Quality are given across the set (1, 3, 5, 7, 10) though five is by far the most common score.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table 2.4: Application Summary Statistics by Race: Out-of-State Applicants

	White			African American			Hispanic			Asian American			Total		
	Reject	Admit	Total	Reject	Admit	Total	Reject	Admit	Total	Reject	Admit	Total	Reject	Admit	Total
Admitted	0.00	100.00	10.91	0.00	100.00	16.74	0.00	100.00	20.18	0.00	100.00	16.60	0.00	100.00	13.52
Female	61.18	55.26	60.53	66.00	66.79	66.13	59.26	60.35	59.48	55.73	54.74	55.56	60.53	57.64	60.14
First-generation college	8.97	7.22	8.78	29.75	19.00	27.95	23.97	14.94	22.14	13.37	8.90	12.63	12.66	9.85	12.28
Legacy	2.63	17.82	4.29	1.78	3.80	2.12	1.25	4.34	1.87	0.80	3.00	1.16	2.11	10.99	3.31
Waiver	3.70	2.63	3.58	36.39	25.67	34.60	18.54	12.63	17.35	9.92	6.63	9.37	8.80	7.42	8.61
Missing SAT or ACT	0.20	0.01	0.18	0.69	0.00	0.57	0.42	0.11	0.35	0.15	0.00	0.12	0.25	0.03	0.22
Missing class percentile	39.68	39.55	39.66	33.06	32.52	32.97	39.49	41.35	39.86	44.33	42.55	44.04	40.16	39.75	40.10
Missing GPA	0.29	0.32	0.30	0.28	0.29	0.28	0.28	0.31	0.29	0.31	0.33	0.31	0.30	0.32	0.30
SAT math (z-score)	-0.01	0.80	0.08	-1.16	-0.08	-0.98	-0.43	0.40	-0.27	0.48	1.20	0.60	-0.06	0.73	0.04
	(0.76)	(0.54)	(0.78)	(0.93)	0.7	(0.99)	(0.86)	(0.61)	(0.88)	(0.77)	(0.41)	(0.77)	(0.89)	(0.67)	(0.90)
SAT verbal (z-score)	0.15	1.02	0.24	-0.91	0.24	-0.72	-0.25	0.64	-0.07	0.22	1.17	0.38	0.04	0.91	0.16
	(0.79)	(0.57)	(0.81)	(0.99)	0.71	(1.04)	(0.88)	(0.64)	(0.91)	(0.85)	(0.57)	(0.88)	(0.89)	(0.66)	(0.91)
High school class percentile (0-100)	87.49	96.75	88.44	77.18	94.01	79.88	83.34	95.34	85.57	86.78	97.14	88.53	85.83	96.22	87.18
	(12.74)	(4.60)	(12.47)	(18.25)	(6.36)	(18.01)	(15.47)	(5.64)	(14.92)	(13.49)	(3.92)	(13.00)	(14.22)	(5.06)	(13.83)
GPA (z-score)	-0.16	0.29	-0.11	-0.70	0.07	-0.57	-0.21	0.37	-0.09	-0.16	0.34	-0.07	-0.21	0.28	-0.15
	(0.74)	(0.62)	(0.74)	(0.99)	(0.64)	(0.99)	(0.89)	(0.73)	(0.89)	(0.75)	(0.59)	(0.75)	(0.79)	(0.64)	(0.79)
Program Rating (1-10)	6.16	8.40	6.40	5.08	7.65	5.51	6.26	8.42	6.70	7.26	9.10	7.57	6.25	8.45	6.55
	(2.56)	(2.00)	(2.60)	(2.67)	(2.31)	(2.78)	(2.80)	(1.98)	(2.79)	(2.50)	(1.58)	(2.47)	(2.64)	(2.00)	(2.67)
Performance Rating (1-10)	7.32	9.08	7.51	5.29	8.01	5.75	6.35	8.58	6.80	6.85	9.06	7.22	6.97	8.88	7.23
	(2.02)	(1.19)	(2.02)	(2.08)	(1.54)	(2.24)	(2.07)	(1.30)	(2.14)	(2.06)	(1.07)	(2.10)	(2.12)	(1.28)	(2.13)
Extracurricular Rating (1-10)	5.87	6.83	5.98	5.24	6.29	5.41	5.57	6.50	5.76	5.81	7.02	6.01	5.79	6.77	5.92
	(1.10)	(0.95)	(1.13)	(1.35)	(1.03)	(1.36)	(1.23)	(0.94)	(1.23)	(1.18)	(1.02)	(1.24)	(1.17)	(1.00)	(1.19)
Essay Rating > 5	0.11	0.44	0.15	0.08	0.30	0.12	0.10	0.35	0.15	0.14	0.50	0.20	0.11	0.43	0.16
Personal Quality Rating > 5	0.16	0.53	0.20	0.19	0.51	0.24	0.20	0.50	0.27	0.17	0.56	0.24	0.17	0.54	0.22
N	56,790	6,954	63,744	7,980	1,605	9,585	7,202	1,821	9,023	13,554	2,698	16,252	91,351	14,281	105,632

Note: Essay and Personal Quality are given across the set (1, 3, 5, 7, 10) though five is by far the most common score.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Within each racial/ethnic group, there is a set of background characteristics that are positively correlated with being admitted. This can be seen in Table 2.3 by comparing the numbers for the first column in each group with the numbers in the second column in each group. Factors that are positively correlated with admission are:

- *Test scores and grades*: Both SAT math and SAT verbal scores are at least half of a standard deviation higher for admits than rejects within each racial/ethnic group. And admits in each group have high school grades that are on average at least a half standard deviation higher than their rejected counterparts.

- *UNC rankings*: Those who are admitted rank substantially higher than those who have been rejected on each of UNC's ranking measures.

- *Legacy*: In each racial/ethnic group, admits are more likely to be children of alums.[28]

As the later models of admission show, these same factors are positively related to admission, even after accounting for other factors. The exception is FGC status; the lower admit rates for these students are driven by these students having lower test scores and ratings. Once I account for differences in academic background and UNC's ratings, FGC status is positively associated with admission.

There are substantial differences in academic qualifications across racial/ethnic groups. Looking at the in-state applicant pool, non-URMs have higher standardized test scores and high-school grades than their URM

[28] These same patterns also hold for out-of-state admits (see Table 2.4) though the difference in grades between accepted and rejected students is in some cases as low as a third of a standard deviation.

counterparts. In particular, Asian-American applicants have higher SAT math scores—over 0.8 of standard deviations higher than Hispanic applicants and more than 1.2 standard deviations higher than African-American applicants. White applicants likewise have substantially higher SAT math scores than URM applicants. Asian and white applicants have SAT verbal scores that are 0.4 higher than Hispanic applicants and almost one standard deviation higher than those of African Americans. The same is true for high school grades. Non-URM applicants have high school grades that are more than 0.3 standard deviations higher than Hispanic applicants and 0.7 standard deviations higher than African American applicants.

UNC's rankings of in-state applicants exhibit similar patterns, as reported in the last set of rows of Table 2.3. On four of the measures–program, performance, extracurricular activities, and essay–Asian-American and white applicants are stronger than their URM counterparts. The one exception is the personal quality rating, where Hispanics are the most highly rated.

For the in-state dataset, then, non-URMs are admitted at a higher rate but also have higher test scores, grades and UNC ratings (with the exception of the personal quality rating). For out-of-state applicants, however, the admit rates for Hispanics were highest and the admit rate for African Americans was higher than that of whites. Yet, Table 2.4 shows that the gaps between URMs and non-URMs with respect to academic qualifications are just as

large in the out-of-state applicant pool as they are in the in-state applicant pool. Out-of-state Asian-American and white applicants have SAT math scores that are 0.85 and 0.35 standard deviations higher than Hispanic applicants, respectively. The gaps between SAT math scores for non-URMs and African Americans is even larger, at 1.5 standard deviation for Asian Americans and 1 standard deviation for whites. In fact, out-of-state Asian-American *rejects* have SAT math scores that are 0.45 standard deviations higher than African-American *admits*.

As with the in-state dataset, out-of-state Asian Americans rank higher on UNC's ratings than their URM counterparts with the exception of the personal quality ratings. For the personal quality rating, Asian Americans have similar scores to African Americans and lower scores than Hispanics. Whites also score higher on all ratings than African Americans with the exception of the personal rating, but they have slightly lower program scores and similar essay scores to Hispanics.

3. Analysis of Race/Ethnicity by Academic Deciles

Given the large differences seen in observed characteristics across races/ethnicities, I first do a simple analysis to examine racial/ethnic differences in admission rates for students with similar academic backgrounds. To do this, I construct an "academic index" by taking a weighted average of the applicant's SAT score and high school GPA. This is done by (i) adding the SAT math and verbal scores, (ii) converting the resulting SAT score to have a mean zero and a standard deviation of one, (iii) converting

high school GPAs to have mean zero and a standard deviation of one for those whose GPA is on a four-point scale, and (iv) adding the two measures together to form the academic index.[29] I then partition the academic index into deciles to show how the patterns of admissions differ by race/ethnicity for students who fall within the same academic index decile.

3.1. Non-URM applicants have significantly higher test scores and grades than URM applicants.

Table 3.1 shows the number and share of each race/ethnicity in each academic index decile for the in-state data. It demonstrates that non-URMs are substantially more academically qualified than URMs. To begin, the first row of Table 3.1 gives the number and share of applicants from each racial group in the bottom decile of the academic index. There are far fewer non-URMs than URMs (by share) in this lowest level of academic qualifications: the share of Asian Americans and whites in the bottom decile are 6.5% and 5.2% respectively; in contrast, 16.9% of Hispanics and 32.7% of African Americans are in the bottom decile. Notably, over 31% of Hispanics and 53% of African-Americans are in the bottom two deciles. Moving to higher deciles shows the share of URMs falling and the share of non-URMs rising. The top decile features 19.8% of Asian-American applicants and 10.7% of white applicants, whereas only 3.7% of Hispanics and less than 1% of African Americans are in the same decile.

[29] Note that approximately 5% of the in-state dataset and approximately 30% of the out-of-state data set either do not have an SAT score (either imputed or actual) or was not graded on a four point scale.

Table 3.1: In-State Number and Share in Each Academic Index Decile by Race/Ethnicity

	Number of applicants in each decile				Share of applicants in each decile			
Decile	White	African American	Hispanic	Asian American	White	African American	Hispanic	Asian American
1	1,848	2,462	582	376	5.18	32.74	16.85	6.54
2	2,762	1,553	518	420	7.74	20.65	14.99	7.31
3	3,310	1,053	476	433	9.27	14.00	13.78	7.53
4	3,663	723	406	473	10.26	9.61	11.75	8.23
5	3,880	563	363	457	10.87	7.49	10.51	7.95
6	3,972	452	325	498	11.13	6.01	9.41	8.66
7	4,101	304	238	588	11.49	4.04	6.89	10.23
8	4,153	205	248	625	11.64	2.73	7.18	10.87
9	4,180	138	171	739	11.71	1.84	4.95	12.86
10	3,820	67	128	1,139	10.70	0.89	3.70	19.82
Total	35,689	7,520	3,455	5,748	100.00	100.00	100.00	100.00

Notes: The academic index decile is based on the sum of two z-scores: one for the applicant's SAT score (math and verbal) and one for GPA.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table 3.2: Out-of-State Number and Share in Each Academic Index Decile by Race/Ethnicity

	Number of applicants in each decile				Share of applicants in each decile			
Decile	White	African American	Hispanic	Asian American	White	African American	Hispanic	Asian American
1	3,033	2,674	840	493	6.77	39.21	13.10	4.41
2	4,195	1,296	787	721	9.36	19.01	12.28	6.45
3	4,618	808	693	816	10.31	11.85	10.81	7.30
4	4,737	603	657	964	10.57	8.84	10.25	8.62
5	4,860	409	645	1012	10.85	6.00	10.06	9.05
6	4,926	308	581	1140	10.99	4.52	9.06	10.19
7	4,883	265	537	1199	10.90	3.89	8.38	10.72
8	4,727	197	562	1386	10.55	2.89	8.77	12.39
9	4,610	136	540	1551	10.29	1.99	8.42	13.87
10	4,216	123	568	1,900	9.41	1.80	8.86	16.99
Total	44,805	6,819	6,410	11,182	100.00	100.00	100.00	100.00

Notes: The academic index decile is based on the sum of two z-scores: one for the applicant's SAT score (math and verbal) and one for GPA.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table 3.2 shows similar disparities in the out-of-state academic indexes between non-URMs and URMs. The share of Asian Americans and whites in

the bottom decile are 4.4% and 6.8% respectively, whereas 13.1% of Hispanics and 39.2% of African Americans are in the bottom decile. Over 58% of African Americans are in the bottom two deciles. As with the in-state sample, the share of URMs drops while the share of non-URMs rise when moving to the higher academic deciles. Ultimately, less than and 8.9% of Hispanics and 2% of African Americans are in the top decile, compared to 17.0% of Asian Americans and 9.4% of whites.

3.2. Admission rates are substantially lower for non-URMs within each academic index decile.

That non-URM applicants tend to have much higher academic qualifications than URM applicants (as measured by the academic index) is relevant only if higher academic indexes are strongly correlated with admission. Table 3.3 demonstrates that this is in fact the case. For the in-state applicant group, admission rates within each academic decile are at least four percentage points lower than the next decile, which demonstrates that admission becomes increasingly likely as the academic index rises. Not only that, but the overall admission rate in the bottom decile is below 1% while in the top decile it is almost 99%. Clearly, then, higher academic indexes are strongly correlated with admission.

Table 3.3: In-State Admission Rates by Academic Index Decile and Race/Ethnicity

Decile	White	African American	Hispanic	Asian American	Total
1	0.70%	1.02%	1.37%	0.27%	0.89%
2	3.08%	10.69%	5.21%	1.90%	5.44%
3	7.76%	28.77%	22.48%	6.24%	13.16%
4	17.83%	49.24%	38.42%	16.91%	23.65%
5	29.56%	71.23%	53.72%	28.67%	35.61%
6	47.31%	80.09%	67.69%	44.38%	51.11%
7	69.40%	88.49%	81.09%	56.97%	69.64%
8	84.08%	94.63%	87.50%	74.40%	83.50%
9	94.07%	97.10%	96.49%	88.36%	93.42%
10	98.85%	97.01%	98.44%	98.16%	98.66%
Total	50.66%	30.25%	40.93%	52.87%	47.33%

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

There are substantial differences, however, between the admissions rates of different racial/ethnic groups within the same academic index decile. With the exception of the top decile (where admission rates are above 97% for every race/ethnicity), URMs have higher admit rates than non-URMs in every decile. But what is striking is how much higher the admission rates are for under-represented minorities. Consider the fifth decile. Non-URMs have admission rates below 30% in this decile. But the corresponding admission rates for URMs are much higher—Hispanic admit rates are over 53% (23 percentage points higher) and African-American admit rates are over 71% (41 percentage points higher). Despite admission rates being higher for Hispanics and African Americans in each decile, the overall admit rates for these groups is lower than for non-URMs, as they are disproportionately in the bottom

deciles of the academic index.

Results for the out-of-state data are shown in Table 3.4. Admission rates in the bottom decile are less than one percent, and in the top decile are 47%. The racial/ethnic discrepancies are even more striking in the out-of-state data than in the in-state data. Here, the overall African-American admit rate is higher than the overall admit rate of whites, and similar to that of Asian Americans—despite substantially more African Americans having academic indexes in the bottom deciles. In the sixth decile, African Americans had over a 46% chance of being admitted. But the corresponding rates for non-URMs was around 5%. Indeed, African Americans in *sixth decile* have admit rates that are over four and a half percentage points higher than whites in the *top decile*. Hispanics too have substantially higher admission rates than non-URMs in deciles beyond the first; the admit rate for Hispanics in the sixth decile was 22%.

Table 3.4: Out-of-State Admission Rates by Academic Index Decile and Race/Ethnicity

Decile	White	African American	Hispanic	Asian American	Total
1	0.49%	0.45%	0.12%	0.00%	0.40%
2	0.52%	5.71%	1.27%	0.28%	1.54%
3	0.89%	14.36%	3.61%	0.25%	2.65%
4	1.52%	29.85%	9.28%	1.04%	4.64%
5	2.90%	39.61%	15.97%	1.38%	6.06%
6	5.34%	46.10%	22.20%	4.56%	8.43%
7	9.24%	57.74%	30.35%	6.51%	12.27%
8	15.87%	57.87%	33.63%	15.51%	18.45%
9	26.51%	69.12%	42.41%	27.66%	28.87%
10	41.58%	73.17%	61.44%	52.89%	46.97%
Total	10.56%	16.67%	19.64%	16.16%	12.91%

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

3.3. Higher academic indexes are associated with higher UNC ratings

I now show that those who have higher academic indexes also tend to have higher scores on each of UNC's ratings. For each of UNC's ratings (program, performance, extracurricular activities, essay, and personal quality), I construct an indicator variable for whether the applicant received a rating above the median. For example, combining both the in-state and out-of-state data sets shows that 50.6% of applicants received a six or lower on the program score. For the program variable, then, an applicant would be given a one (i.e., above the median) if she scored a seven or higher on the program rating, and a zero otherwise.

Table 3.5 reports the share of each academic index decile that has a

rating above the 50th percentile for each of UNC's ranking measures separately for the in-state and out-of-state datasets. Not surprisingly, the share receiving a rating above the median for the program and performance ratings rises substantially with each decile of the academic index for both data sets. For example, the share of those in the bottom decile with program ratings above the median is 15% in the in-state sample, but rises to 89% in the top decile. The same is true for performance: the share above the median in the bottom decile is 1.8%, but rises to the 84.4% in the top decile.

Table 3.5: Share above Median Rating by Academic Index Decile

	In-State					Out-of-State				
Decile	Program	Perform	Activities	Essay	Personal Qualities	Program	Performance	Activities	Essay	Personal Qualities
1	15.0%	1.8%	8.4%	2.0%	11.0%	15.3%	3.9%	12.5%	3.4%	11.3%
2	22.6%	7.7%	12.6%	3.7%	13.1%	25.6%	15.5%	18.1%	6.8%	13.1%
3	31.3%	14.1%	15.6%	5.2%	14.5%	34.0%	26.6%	21.1%	8.4%	14.7%
4	36.3%	21.7%	18.3%	6.5%	15.8%	40.7%	38.4%	25.6%	10.3%	16.6%
5	43.2%	31.8%	20.4%	8.9%	17.7%	48.2%	47.5%	28.0%	13.0%	18.3%
6	50.1%	40.8%	22.1%	9.3%	17.9%	56.4%	54.4%	31.4%	14.9%	20.6%
7	57.9%	51.3%	24.5%	10.6%	19.7%	64.8%	62.9%	34.3%	18.0%	23.4%
8	65.2%	61.5%	26.7%	12.9%	21.0%	72.0%	68.6%	38.2%	20.2%	26.9%
9	74.6%	70.5%	32.1%	15.5%	22.5%	79.0%	74.8%	41.8%	24.1%	30.2%
10	88.7%	84.4%	40.4%	22.2%	28.7%	85.9%	82.1%	47.2%	29.7%	35.3%
Total	48.4%	38.4%	22.1%	9.6%	18.2%	52.0%	47.2%	29.7%	14.8%	21.0%

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Higher academic indexes are also positively correlated with UNC's extracurricular activity, essay, and personal quality ratings. Among in-state applicants, the share above the median on extracurricular activities is 8.4% in the bottom decile, but 40% in the top decile; for the essay the rate is 2% in the bottom decile and 22% in the top decile; and for personal qualities the

rate is 11% in the bottom decile and 29% in the top decile. Similar gaps are seen in the out-of-state sample. It follows that those who are strong academically also tend to be strong on non-academic measures.

3.4. Basing admission on the academic index would substantially affect the racial/ethnic distribution of the admitted class.

In this section, I examine how the admitted class would change if the academic index was the only consideration in admissions decisions. Although the factors that make up the academic index are not the only considerations in UNC's admissions decisions, the academic index is highly correlated with both UNC's ratings of applicants and the ultimate decision whether to admit or deny applicants.[30] Determining what the admitted class would look like if the academic index were the only consideration enables me to establish a benchmark for how accounting for other non-race-based characteristics affect estimates of the removal of race-based preferences.

First, consider in-state applicants. Over the course of the six-year period, the in-state dataset includes 24,808 admitted students who had valid test score information, had high-school grades measured on a four-point scale, and were one of the four major racial/ethnic groups. Table 3.6 shows the number of admits and share of the admitted class by race under different admission scenarios. The first row of Table 3.6 shows the actual racial/ethnic distribution of admits for this group as well the share of the admitted class

[30] See Table 3.5.

four each of the four major racial/ethnic groups. Whites, African Americans, Hispanics, and Asian Americans make up 72.9%, 9.2%, 5.7%, and 12.3% respectively of the admitted class from this group of applicants.

The second row of Table 3.6 shows how the admitted class would change if admission was based solely on taking those from the highest deciles of the academic index, holding fixed the number of admits at 24,808. In this case, all applicants from deciles seven through ten would be admitted as would a random 75.6% of those in decile six. The number of admitted white and Asian-American applicants would increase by 1175 and 428 respectively, resulting in the share of the admitted class for white and Asian-American applicants increasing by 4.7 and 1.7 percentage points respectively.[31] These gains for white and Asian-American applicants would correspond with equally large admission losses for Hispanic and African-American applicants, especially for the former. The number of African-American and Hispanic admits would fall by 383 and 1,220, respectively. The shares of the admitted class for Hispanic and African-American applicants thus would fall by 1.5 and 4.9 percentage points, respectively.

[31] Note that this is an underestimate of the total effect because approximately 5% of the in-state dataset either does not have an SAT score or was not graded on a four-point scale.

Table 3.6: Number and Share of In-State Admits under Different Admissions Scenarios Based on Deciles of the Academic Index

	Number of Admits				Share of admits				
	White	African American	Hispanic	Asian American		White	African American	Hispanic	Asian American
Actual	18,080	2,275	1,414	3,039	Actual	72.9%	9.2%	5.7%	12.3%
Top	19,255	1,055	1,031	3,467	Top	77.6%	4.3%	4.2%	14.0%
Random 5	19,231	1,109	1,055	3,413	Random 5	77.5%	4.5%	4.3%	13.8%
Random 6	19,073	1,368	1,165	3,201	Random 6	76.9%	5.5%	4.7%	12.9%
Random 7	18,812	1,661	1,273	3,061	Random 7	75.8%	6.7%	5.1%	12.3%
Random 8	18,405	2,076	1,395	2,933	Random 8	74.2%	8.4%	5.6%	11.8%
Random 9	17,808	2,662	1,512	2,827	Random 9	71.8%	10.7%	6.1%	11.4%
Random 10	16,893	3,559	1,635	2,721	Random 10	68.1%	14.3%	6.6%	11.0%

Notes: The label "Random X" refers to a model in which applicants from the top X deciles are selected randomly via lottery.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

The next set of rows of Table 3.6 shows how the distribution of the admitted class would change if admissions were conducted by lottery among those of a minimal level of academic qualifications (specifically, conditional on being in a particular academic index decile or above). Extending this lottery to lower academic index deciles would result in higher shares of African Americans and Hispanics. However, the number of under-represented minority admits would not exceed the actual number of under-represented minority admits unless the lottery were to include the top nine academic index deciles; lotteries including only the top eight deciles would result in lower shares of URM admits.

Repeating this exercise with the out-of-state dataset produces more striking results. Similar to Table 3.6, the first row of Table 3.7 shows the number and share of the admitted class for out-of-state applicants who had

valid test score information, high-school grades measured on a four-point scale, and were one of the four major racial/ethnic groups. The total number of admits for this group over the six years of data was 8,933 and the overall admit rate was 12.9%. Whites, African Americans, Hispanics, and Asian Americans make up 52.9%, 12.7%, 14.1%, and 20.2% respectively of the admitted class from this group of applicants.

As shown in the second row of Table 3.7, admissions based solely on academic index decile would result in all applicants in the top decile being admitted and 27.7% of those in the next decile. This would have resulted in 920 and 575 more white and Asian-American admits, respectively.[32] The share of the admitted out-of-state class would rise by 10.3 percentage points for whites and by 6.4 percentage points for Asian Americans. The number of Hispanic and African American admits would fall by 523 and 972 respectively.

[32] Note that this is an underestimate of the total effect because 30% of the out-of-state dataset either does not have an SAT score or was not graded on a four-point scale.

Table 3.7: Number and Share of Out-of-State Admits under Different Admissions Scenarios Based on Deciles of the Academic Index

	Number of Admits				Share of Admits			
	White	African American	Hispanic	Asian American	White	African American	Hispanic	Asian American
Actual	4,730	1,137	1,259	1,807	52.9%	12.7%	14.1%	20.2%
Top	5,650	165	736	2,382	63.2%	1.9%	8.2%	26.7%
Random 2	5,779	170	725	2,259	64.7%	1.9%	8.1%	25.3%
Random 3	5,901	199	727	2,106	66.1%	2.2%	8.1%	23.6%
Random 4	6,011	235	720	1,968	67.3%	2.6%	8.1%	22.0%
Random 5	6,075	268	725	1,866	68.0%	3.0%	8.1%	20.9%
Random 6	6,107	311	743	1,772	68.4%	3.5%	8.3%	19.8%
Random 7	6,103	378	757	1,695	68.3%	4.2%	8.5%	19.0%
Random 8	6,084	461	774	1,614	68.1%	5.2%	8.7%	18.1%
Random 9	6,002	596	800	1,536	67.2%	6.7%	9.0%	17.2%
Random 10	5,783	880	827	1,443	64.7%	9.9%	9.3%	16.2%

Notes: The label "Random X" refers to a model in which applicants from the top X deciles are selected randomly via lottery.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

The next set of rows of Table 3.7 shows how the admitted class would change if admissions were a lottery conditional on being in a particular academic index decile or above. Even randomly drawing from the top five academic index deciles[33] would result in dramatic shifts of the racial/ethnic composition of the admitted class. The share of the admitted class that was Hispanic would fall from 14.1% to 8.1%. African Americans make up 12.7% of the out-of-state admits for this group of students; their share would be 3% under a lottery over the top five deciles.

UNC, of course, bases its admissions on more than academics. So in the

[33] As shown in Table 3.4, admit rates for whites and Asian Americans in the sixth decile are 5.3% and 4.6%.

abstract, it is possible that URM applicants are stronger on other non-race-based characteristics that UNC values and these figures therefore overstate how removing race-based preferences would affect the composition of the admitted class. The rest of this report highlights how controlling for additional characteristics affects the estimated impact of removing race-based preferences.

4. Estimates of Racial/Ethnic Preferences in Admissions

Tables A.4.1 and Table A.4.2. show estimates of a series of logit models of admission for the in-state and out-of-state dataset, respectively. Figure 4.1 lists the controls that each model includes. Each successive model includes more controls than the preceding one.

Figure 4.1: Controls Used for Different Models of UNC's Admissions Decisions

Model 1	Race/ethnicity, female, early or regular decision, alum, first generation, fee waiver, missing fee waiver, and year indicators
Model 2	Model 1 plus SAT math*; SAT verbal*; missing SAT times race/ethnicity; GPA*; missing GPA times race/ethnicity; percentile; percentile times non-standard rank type, missing percentile times year; race/ethnicity; non-standard rank type; non-standard rank type times race/ethnicity; indicators for different ways of imputing SAT *indicates variable was z-scored, GPA is only for those on a 4pt scale
Model 3	Model 2 plus indicators for UNC program, performance, activity, essay, and personal quality score
Model 4	Model 3 plus intended college major; female interacted with race/ethnicity; first-generation interacted with race/ethnicity
Model 5	Same as model 4 but only for the set of students from high schools that had a minimum number of applications and admits
Model 6	Model 5 plus high school fixed effects
Model 7	Same as model 6 but only for the set of students with census tract data who had a minimum number of applications and admits *Note this is only for the in-state models

4.1. Estimates of racial/ethnic preferences in admissions for in-state applicants

Considering first the in-state dataset, the base model with no controls for academic preparation show negative coefficients for African Americans and Hispanics and a positive coefficient on Asian American.[34] This is consistent with Table 2.1, which showed that African Americans and Hispanics had lower admit shares than application shares when considering

[34] These negative coefficients are relative to whites, where the white coefficient is normalized to zero.

in-state applicants. Adding test scores and grades (column 2) dramatically changes the picture: now the coefficients on African American and Hispanic are both large and positive, with the coefficient on Asian-American small and insignificant. This change in the patterns occurs because Asian-American in-state applicants have significantly higher grades and test scores than their African-American and Hispanic counterparts. Even with limited controls, the estimated preferences are substantial. For example, the admit rate for an Asian-American applicant whose observables would imply a 25% chance of being admitted would increase to over 53% if the applicant was given the same preference as a Hispanic applicant and to over 66% if the applicant was treated as an African-American applicant.

However, as shown in the columns 3 through 8, the estimated preferences in column 2 are *underestimates* of the preference URMs receive over non-URMs. Adding controls for UNC's ranking of the applicants (column 3), allowing for demographic heterogeneity and controlling for intended major (column 4), adding controls for high school attended (high school fixed effects) (column 6), and adding controls for census tract all substantially *increase* the coefficients on African American and Hispanics.

Columns 4 through 8 show that the magnitude of the admissions preference in-state URM applicants receive also depends on gender and FGC status. Particularly striking are the interactions with FGC status. Column 4 shows that the magnitude of the FGC preference is less than 30% of the

magnitude of the racial preference African-American male applicants receive. However, first-generation URM applicants do not receive the same FGC preference as white students. First-generation Hispanic applicants receive a preference for FGC status that is 25% to 50% smaller in magnitude than the FGC preference received by white students depending on the model.[35] More striking is that first-generation, in-state African-American applicants do not receive any preference for their FGC status.[36] These results show that racial preferences are stronger for those who are not FGC than for those who are FGC. To illustrate, consider two applicants, one who is African American and one who is non-URM. Relative to the non-URM applicant, the overall preference the African-American applicant receives would be larger if the two applicants were non-FGC than if they were FGC.[37]

To better understand the magnitude of racial/ethnic preferences, as well how the magnitude varies with gender and first-generation college status, Table 4.1 shows how Asian-American and white students' admissions

[35] The interaction between FGC status and Asian American is small and insignificant, implying that the effect of FGC status for Asian-American applicants is similar to the effect of FGC status for whites.

[36] The negative coefficient on the interaction cancels out the base preference for FGC status.

[37] The interaction of FGC status and race for in-state URM applicants could be viewed another way—specifically as first-generation URM applicants receiving a "full" FGC preference but receiving a diminished racial preference compared to their non-FGC URM counterparts. Either way, it is apparent that UNC treats first-generation URMs no differently than non-first-generation URMs, which (as explained above) disadvantages first-generation URMs (relative to non-first-generation URMs) when compared against non-URMs.

chances would change had they been treated like African Americans or Hispanics. These predicted changes use the estimates from models 4, 6, and 8, showing results for Asian Americans in the first panel and results for whites in the second panel.

The first row of Table 4.1 considers an in-state male Asian American who was not first generation and whose observed characteristics (e.g. test scores, grades, etc.) would give him a 25% chance of admission. The first entry shows how his admissions chances would change using the estimates from model 4. Using the estimates from column 4 shows his chances would increase to 63.8% if treated as a Hispanic applicant. If he were instead treated as an African-American applicant, his admission chances would increase to 88.9%. The next row considers an Asian American applicant with the same characteristics but now with a 10% chance of admission. His probability of admission would increase to 72.7% if treated as an African American using the estimates from model 4.[38] In other words, these hypothetical non-URM applicants who are highly likely to be rejected *would be transformed into highly likely admits if they were URMs, and all other characteristics stayed the same*.

[38] The effects would be slightly larger if the hypothetical student were white rather than Asian American.

Table 4.1: The Magnitude of Racial/Ethnic Preferences for In-State Applicants

	Original admit probability	Admission probability if treated as:					
		African American			Hispanic		
		Model 4	Model 6	Model 7	Model 4	Model 6	Model 7
Asian American							
Male, not FGC	25%	88.85%	93.61%	96.85%	63.76%	74.64%	79.60%
	10%	72.65%	83.00%	91.11%	36.96%	49.52%	56.54%
Female, not FGC	25%	86.92%	91.95%	95.54%	66.85%	78.34%	80.86%
	10%	68.90%	79.20%	87.71%	40.20%	54.66%	58.48%
Male, FGC	25%	78.19%	82.49%	89.23%	59.81%	62.75%	71.41%
	10%	54.44%	61.09%	73.41%	33.16%	35.96%	45.43%
Female, FGC	25%	74.93%	78.60%	85.23%	63.04%	67.43%	73.00%
	10%	49.90%	55.04%	65.79%	36.25%	40.83%	47.40%
White							
Male noFGC	25%	91.56%	94.50%	97.31%	70.53%	77.55%	82.12%
	10%	78.33%	85.14%	92.34%	44.37%	53.52%	60.49%
Female noFGC	25%	87.47%	90.22%	95.00%	67.94%	74.50%	78.93%
	10%	69.95%	75.46%	86.36%	41.39%	49.34%	55.54%
Male FGC	25%	81.03%	85.29%	89.88%	63.95%	67.47%	72.82%
	10%	58.75%	65.90%	74.76%	37.15%	40.88%	47.17%
Female FGC	25%	73.34%	75.68%	82.34%	61.10%	63.70%	68.61%
	10%	47.84%	50.92%	60.85%	34.36%	36.90%	42.14%

Notes: Model 4 controls for applicant demographic and academic characteristics and ratings. Model 6 includes the same controls as Model 4 plus high school fixed effects. Model 7 includes the same controls as Model 4 plus high school and census tract fixed effects. See Appendix Table A.4.1 for details.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx, UNC0379830.xlsx, UNC0379831.xlsx, UNC0379832.xlsx, UNC0379833.xlsx, UNC0379838.xlsx.

Adding high school fixed effects (model 6) and census tracts (model 7) substantially increases the estimated magnitude of racial preferences as shown in the second and third columns. These models account for unobserved differences in high school quality and other unobserved variables that are correlated with location. An in-state male Asian-American applicant with a 25% chance of admission would see his admissions chances increase to 93.6%

and 96.9% if treated as an African American based on the estimates of models 6 and 7, respectively. And model 7 predicts that an Asian-American applicant with a 10% chance of admission would see his probability jump to 91.1% if he was instead treated as an African American. That is, *changing only the race of this hypothetical Asian-American male applicant—and keeping all other factors the same—would transform him from being a highly likely reject to a near-certain admit*.[39]

Because African-American females and first generation African Americans receive a smaller overall preference than African American males who are not first generation, the gains for non-URMs are smaller–but nonetheless substantial–in the remaining rows of the top panel. To illustrate, an Asian-American female applicant with first-generation status and a 25% chance of admission would see her probability of admission increase to 74.9% and 78.6% if she were treated as an African-American applicant (based on the estimates of models 4 and 6, respectively). And her probability of admission would increase to 85% based on the estimates of model 7.[40] These comparisons underscore the impact that race has on an applicant's chances of admission.

[39] As with the previous illustration, the results are slightly larger if the hypothetical were a white applicant rather than an Asian-American applicant.

[40] The gains would be slightly smaller if the hypothetical applicant was white instead of Asian American, at 73.4%, 75.5%, and 82.1% for models 4, 6, and 8 respectively.

4.2. Estimates of racial/ethnic preferences in admissions for out-of- state applicants

Table A.4.2 repeats the analysis of Table A.4.1 but for the out-of-state dataset. Column 1, which only controls for demographics and year indicators, shows all three non-white groups with positive coefficients. This is again consistent with Table 2.1, which showed that admit rates for out-of-state whites were lower than for other groups. Adding controls for test scores and grades (column 2) shrinks the positive and significant relationship between Asian American and admissions but substantially increases the relationship between being Hispanic or African American and admissions, consistent with test scores and grades having a positive effect on admissions and Hispanics and African American having lower test scores and grades.

Again considering a hypothetical non-URM applicant and changing only that applicant's race illustrates the magnitude of the racial boost given to URM applicants over non-URM applicants in the admissions process. For example, column 2 shows that an out-of-state Asian-American applicant with a 25% chance of admission would have her chances of admission increase to more than 74% if she were treated as a Hispanic applicant and more than 96% if she were treated as an African-American applicant.

As with Table A.4.1, adding controls substantially increases the estimates of racial/ethnic preferences for under-represented minorities. To get a sense of the magnitude of racial/ethnic preferences, I repeat the analysis in Table 4.1 using the estimates from models 4 and 6 of Table A.4.2. Results are

shown in Table 4.2. The estimated racial/ethnic preferences are substantially larger here than in the in-state sample.

Table 4.2: The Magnitude of Racial/Ethnic Preferences for Out-of-State Applicants

	Original admit probability	Admission probability if treated as:			
		African American		Hispanic	
		Model 4	Model 6	Model 4	Model 6
Asian American					
Male, not FGC	25%	99.23%	99.69%	85.13%	89.72%
	10%	97.72%	99.08%	65.61%	74.43%
Female, not FGC	25%	99.22%	99.70%	88.07%	91.86%
	10%	97.70%	99.10%	71.11%	79.00%
Male, FGC	25%	98.33%	99.29%	78.39%	83.98%
	10%	95.14%	97.90%	54.74%	63.61%
Female, FGC	25%	98.31%	99.31%	82.39%	87.15%
	10%	95.10%	97.95%	60.94%	69.32%
White					
Male noFGC	25%	99.30%	99.75%	86.41%	91.56%
	10%	97.94%	99.26%	67.94%	78.35%
Female noFGC	25%	99.36%	99.77%	90.05%	93.57%
	10%	98.11%	99.30%	75.10%	82.90%
Male FGC	25%	97.56%	98.90%	71.14%	77.06%
	10%	93.01%	96.77%	45.10%	52.82%
Female FGC	25%	97.76%	98.96%	77.82%	81.82%
	10%	93.57%	96.95%	53.90%	60.01%

Notes: Model 4 controls for applicant demographic and academic characteristics and ratings. Model 6 includes the same controls as Model 4 plus high school fixed effects. See Appendix Table A.4.2 for details.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Asian-American applicants with a 25% probability of admission would see their probabilities increase to between 78% to 92% if they were treated as Hispanic applicants, depending on the gender and first generation status of the applicant as well as whether the model included high school fixed effects.

The corresponding estimates for whites range from 71% to 93%, with lower gains in the case where the applicant is first generation.

The effect of being treated as an African American is even more dramatic. Asian-American applicants who have a 25% probability of admission based on their observed characteristics would have an over 98% and over 99% of probability of admission based on models 4 and 6, respectively, regardless of their gender or first generation status. The similar probabilities for white students are almost as high—over 97% and 98% for the two models. Indeed, Asian Americans with a 10% chance of admission would see their probabilities rise to over 95% and 97% for models 4 and 6 respectively.

Similar to the results from the in-state dataset, African-American and Hispanic students do not receive as much of a bump from first generation status as their Asian-American and white peers. Although unlike the in-state dataset African Americans still see a bonus from being first generation, the bonus for both African Americans and Hispanics is less than half that of other races/ethnicities.

4.3. Preferences for socioeconomic status and legacy

As noted with regard to first generation status, preferences occur on other dimensions besides race/ethnicity. The preference white students receive from FGC status in both the in-state and out-of-state datasets is around one-third of the effect of being African American and two-thirds that

of being Hispanic. Because racial preferences are higher in the out-of-state data set, this implies that preferences for FGC are also higher in the out-of-state data set.

The benefits of FGC status are smaller for URM applicants than their non-URM counterparts. As noted above, for in-state applicants, African-American applicants receive no preference for FGC status and Hispanic applicants receive a FGC preference of substantially diminished magnitude. Out-of-state African-American applicants receive a preference for FGC that is 70% lower than that received by their white counterparts. Hispanic FGC applicants receive a boost that is half that of white FGC applicants in both the in-state and out-of-state datasets.

Legacy applicants also receive a preference, though the size of the preference differs dramatically between in-state and out-of-state applicants. The likelihood of admission for an in-state, non-legacy applicant with a 25% chance of admission would increase to 32% and 36% if treated as a legacy for models 4 and 6, respectively. But in the out-of-state dataset, legacy preferences are almost as large as the racial preferences given to African-American applicants. For the hypothetical out-of-state, non-legacy applicant with a 25% chance of admission, changing the applicant to legacy status would increase the likelihood of admission to more than 97%. This is consistent with the results in Table 2.4, which showed that although only 3.3% of the out-of-state dataset are legacies, legacies make up almost 11% of

out-of-state admits.[41]

4.4. Average effects of racial/ethnic preferences

The previous analysis focused on how applicants with particular admission probabilities would see their odds change with a change in their characteristics. In Table 4.3 I show how the average probability of admission would change for Asian Americans and whites if they were treated as African Americans and Hispanics. This is done for the models in columns (4) through (6) of Tables A.4.1 and A.4.2 and, for the in-state dataset, the model in column (8).

The first panel of Table 4.3 shows how non-URM students would see their admissions probabilities change if they had been treated like African Americans and Hispanics in the admissions process. The second and third panels show the results for Asian-American and white applicants, broken out separately.

Admission rates for in-state, non-URM applicants would increase by over ten percentage points if they were treated as Hispanics in each of the four models. The increase in admit rate would rise to more than sixteen percentage points if non-URMs were treated as African Americans.

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[41] This is generally consistent with the testimony of the admissions officers, who said "[b]y design, we ask our readers not to worry about alumni status when reviewing an in-state student" but for out-of-state students, [i]t can make a difference . . . there is a higher admit rate for children of alumni than the general out-of-state admit rate overall." Rosenberg Depo. 264:10-25; *see also* Farmer Depo. 279:5-15 ("Q. Is legacy preference one of those main factors that you may consider in the admissions process? A. It can be, primarily for non-resident students.").

Table 4.3: Predicted Admissions Probabilities for Asian Americans and Whites if Treated as African American or Hispanic

	Original admit probability	Treated as African: Adjusted admit probability	Treated as African: Change in admission probability	Treated as Hispanic: Adjusted admit probability	Treated as Hispanic: Change in admission probability	Observations
Non-URM						
In-State						
No high school fixed effects	0.512	0.685	0.172	0.620	0.108	43,111
High school fixed effects sample	0.515	0.686	0.171	0.623	0.108	41,797
High school fixed effects	0.515	0.678	0.163	0.622	0.107	41,797
HS and Census tract fixed effects	0.525	0.705	0.181	0.636	0.122	30,946
Out-of-State						
No high school fixed effects	0.121	0.569	0.448	0.323	0.202	79,752
High school fixed effects sample	0.134	0.592	0.458	0.349	0.215	55,835
High school fixed effects	0.134	0.555	0.421	0.330	0.196	55,835
Asian American						
In-State						
No high school fixed effects	0.536	0.680	0.144	0.625	0.089	6,017
High school fixed effects sample	0.557	0.706	0.149	0.650	0.093	5,633
High school fixed effects	0.557	0.704	0.147	0.655	0.098	5,633
HS and Census tract fixed effects	0.556	0.700	0.144	0.652	0.096	4,257
Out-of-State						
No high school fixed effects	0.167	0.623	0.456	0.383	0.217	16,202
High school fixed effects sample	0.189	0.667	0.478	0.424	0.225	12,178
High school fixed effects	0.193	0.658	0.465	0.415	0.208	12,178
White						
In-State						
No high school fixed effects	0.509	0.685	0.177	0.620	0.111	37,094
High school fixed effects sample	0.524	0.703	0.180	0.638	0.114	35,060
High school fixed effects	0.524	0.694	0.171	0.636	0.112	35,060
HS and Census tract fixed effects	0.533	0.705	0.171	0.646	0.113	25,951
Out-of-State						
No high school fixed effects	0.109	0.555	0.446	0.307	0.198	63,550
High school fixed effects sample	0.131	0.612	0.481	0.356	0.225	43,814
High school fixed effects	0.135	0.598	0.463	0.347	0.212	43,814

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx. UNC0379830.xlsx, UNC0379831.xlsx, UNC0379832.xlsx, UNC0379833.xlsx, UNC0379838.xlsx

Consistent with the previous results, the changes in the out-of-state

admissions rates are much larger. If non-URM applicants were treated as Hispanic applicants, their admission rates would rise by more than nineteen percentage points, more than doubling their original admit rate. And if non-URM applicants were treated as African Americans, their admission rates would increase by over 42 percentage points, more than quadrupling their original admit rate. Given capacity constraints, these sorts of admission rates would not be sustainable, but this analysis serves to illustrate the extent of racial preferences in the out-of-state pool.

4.5. Capacity Constraints

As discussed in the previous section, capacity constraints would not permit a rise in non-URM admit rates to those of their URM counterparts. There simply would not be enough slots for all the admitted students. Accordingly, I now calculate how the admitted pool would change in the absence of racial/ethnic or legacy preferences, taking into account capacity constraints. To do this, I assume that the number of admits will remain the same with and without racial/ethnic preferences. I then estimate model 4 separately by year. I then shut off both the baseline effect of race/ethnicity as well as the interactions between female and FGC status with race/ethnicity. For each year, the estimated intercept is then raised until the mean probability of admission is the same with and without the preferences in question.[42]

[42] Results for the yearly logit models are presented in Tables A.4.5 & A.4.6.

The first panel of Table 4.4 shows number of in-state admits and share of the admitted class for each of the four main racial/ethnic groups in the data. The second panel shows the predicted number of admits and shares in the absence of racial preferences. Over the full six-year period, the model predicts that the number of the Asian Americans admitted would rise by 110, a 3.3% increase. The number of white admits would increase by 5.8%, an additional 1109 admits. On the other hand, fewer African-American and Hispanic applicants would be admitted. African-American and Hispanic admits would fall by 864 and 273, respectively (in terms of percentages, by 36% and 19%).

Table 4.4: In-State Admissions Probabilities under Counterfactual Regimes

	Number of admits	Share of admits
Data		
White	18,865	68.8%
African American	2,374	8.7%
Hispanic	1,470	5.4%
Asian American	3,223	11.8%
Total	27,422	
No racial preferences		
White	19,974	72.8%
African American	1,510	5.5%
Hispanic	1,197	4.4%
Asian American	3,333	12.2%
No legacy preferences		
White	18,818	68.6%
African American	2,390	8.7%
Hispanic	1,481	5.4%
Asian American	3,239	11.8%
No racial or legacy preferences		
White	19,932	72.7%
African American	1,525	5.6%
Hispanic	1,209	4.4%
Asian American	3,349	12.2%

Notes: See Table A.4.3 in the Appendix for details.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

The third panel of Table 4.4 removes in-state legacy preferences. Since legacy preferences are not very strong for the in-state sample, there is little effect on racial/ethnic rates. The fourth panel removes both racial preferences and legacy preferences. The results look very similar to the second panel, though the increase in Asian American admits rises to 3.9%, illustrating that racial preferences have a much greater impact

than legacy preferences on admissions decisions.

Table 4.5 repeats the analysis of Table 4.4, but for out-of-state instead of in-state applicants. As the table illustrates, the effects for out-of-state applicants are much larger. The model predicts that 544 more Asian Americans would be admitted, a 20% increase. The percentage increase is even higher for whites at 28%, resulting in 1938 more admits. The number of African American and Hispanic admits plummet, falling by 1395 and 1079, 87% and 59% drops, respectively.

Removing legacy preferences would increase the number of out-of-state Asian American admits by 143, a 5.3% increase. Removing legacy preferences would also increase the number of URM admits, but by smaller margins. The increases for African American and Hispanic admits would be 53 and 59, approximately 3.3% increases for each. On the other hand, the number of white admits would fall by 280, a 4% decrease.

Removing both sets of preferences would increase the number of out-of-state Asian American admits by 706, a 26% increase. White admits would increase by 25%—1731 more admits. The drop in African American and Hispanics admits would be 1393 and 1054—87% and 58% drops, respectively. Again, this demonstrates that racial preferences have a far greater impact than legacy preferences on admissions decisions.

Table 4.5: Out-of-State Admissions Probabilities under Counterfactual Regimes

	Number of admits	Share of admits
Data		
White	6,954	48.7%
African American	1,605	11.2%
Hispanic	1,821	12.8%
Asian American	2,698	18.9%
Total	14,281	
No racial preferences		
White	8,892	62.2%
African American	210	1.5%
Hispanic	742	5.2%
Asian American	3,242	22.7%
No legacy preferences		
White	6,678	46.7%
African American	1,658	11.6%
Hispanic	1,880	13.2%
Asian American	2,841	19.9%
No racial or legacy preferences		
White	8,685	60.8%
African American	212	1.5%
Hispanic	767	5.4%
Asian American	3,404	23.8%

Notes: See Table A.4.4 in the Appendix for details.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

5. My Estimates of the Magnitude of Racial/Ethnic Preferences Likely are Understated

There are at least two reasons why my estimates of the magnitude of racial/ethnic preferences are, if anything, understated. First, my estimates show that Asian Americans and whites are stronger on observed measures that are associated with higher admissions probabilities. Second, there is

evidence of preferences in favor of African Americans and Hispanics in UNC's personal quality rating. Correcting for these preferences would result in even larger estimates of racial/ethnic preferences.

5.1. Selection on observables and unobservables

One of the advantages of the UNC dataset is that the set of observed characteristics is more robust than what is typically available. Many peer-reviewed studies in excellent journals have been published analyzing discrimination with data of much lower quality. But there is nonetheless the issue, which is faced by all discrimination studies using observational data, of whether accounting for unobserved characteristics would eliminate the finding of a penalty against Asian Americans.

To measure selection on observables in admissions, an index is formed using all of the coefficients from model 4 except for race and year. This index, when coupled with race and year, is what is used to predict the admissions probabilities. Decoupling race and year from the index leads to a ranking of applicants based on their observed characteristics.

The first quadrant of Table 5.1 shows how the African-American applicant and admit pool compare to the Asian-American applicant and admit pool. The first column shows where the median African American's index lies on the Asian-American distribution. For in-state applicants, the median African American lies between the 17th and 19th percentile. For out-of-state applicants, the median African American is between the 9th and 14th

percentile depending on the model. This reveals two key facts: (i) based on observed characteristics, Asian-American applicants are substantially stronger than African-American applicants and (ii) this is especially true in the out-of-state dataset. The second column of Table 5.1 shows where the median African-American admit lies on the Asian-American admit distribution. In terms of observable characteristics, the median African-American admit in the in-state dataset would fall between the 8th and the 10th percentile. And for the out-of-state data the median African-American admit falls below the 1st percentile of the Asian-American distribution, introducing massive distortions in the characteristics of the African Americans and Asian Americans who are admitted.

Table 5.1: Where African American and Hispanic Applicants and Admits Fall on the Asian American and White Admissions Index Distribution

	Median African American		Median Hispanic		
	Percentile of Applicant Dist	Percentile of Admit Dist	Percentile of Applicant Dist	Percentile of Admit Dist	Observations
Asian American					
In-State					
No high school fixed effects	19%	9%	31%	21%	6,017
High school fixed effects sample	18%	10%	30%	20%	5,633
High school fixed effects	18%	10%	30%	20%	5,633
HS and Census tract fixed effects	17%	8%	31%	20%	4,257
Out-of-State					
No high school fixed effects	9%	<1%	30%	8%	16,202
High school fixed effects sample	9%	<1%	31%	8%	12,178
High school fixed effects	14%	<1%	33%	8%	12,178
White					
In-State					
No high school fixed effects	16%	10%	30%	24%	37,094
High school fixed effects sample	17%	10%	31%	23%	35,060
High school fixed effects	18%	11%	31%	25%	35,060
HS and Census tract fixed effects	17%	9%	32%	23%	25,951
Out-of-State					
No high school fixed effects	12%	3%	37%	11%	63,550
High school fixed effects sample	11%	2%	37%	11%	43,814
High school fixed effects	19%	2%	42%	9%	43,814

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx, UNC0379830.xlsx, UNC0379831.xlsx, UNC0379832.xlsx, UNC0379833.xlsx, UNC0379838.xlsx.

Table 5.1 also shows where the median Hispanic applicant and admit falls on the corresponding Asian-American distribution. Here, where the median Hispanic applicant lies on the Asian American distribution is similar between in-state and out-of-state applicants at slightly over the 30th percentile. This again shows the positive selection of Asian Americans relative to Hispanic Americans based on observed characteristics, though the

discrepancies are not as large as between Asian Americans and African Americans. As with African Americans, the median Hispanic admit is at a lower percentile of the Asian American admit distribution than what was seen for applicants. For the in-state dataset, the median Hispanic admit falls at the 20th percentile of the Asian American admit distribution; for the out-of-state dataset the median Hispanic admit falls at the 8th percentile.

The second panel of Table 5.1 considers where African Americans and Hispanics fall on the white distribution, both for applicants and admits. For the in-state dataset, where African-American and Hispanic applicants and admits fall on the white distribution mirrors what was seen for Asian Americans. Hence the in-state sample shows whites are stronger on observable characteristics and that this is especially true for admits. The out-of-state sample shows the same qualitative patterns as what was seen for Asian Americans but the disparities are slightly smaller. For example, the median out-of-state African American admit is at the 2nd or 3rd percentile of the corresponding white distribution but at less than the first percentile of the Asian American admit distribution.

Given the substantial differences in the observed characteristics between under-represented minorities and their Asian American and white counterparts in ways that favor the latter group, there is no reason to assume that the unobservable characteristics to go in the opposite direction. Hence to the extent that selection on observables is indicative of selection on

unobservables, Asian Americans and whites are likely stronger on those characteristics as well, implying I am underestimating African American and Hispanic advantages.

5.2. Ratings components and race/ethnicity

Another potential avenue for race/ethnicity to matter is through the profile rankings assigned by UNC admissions officers to each file. To examine how race/ethnicity affects profile rankings, a series of ordered logits are estimated for each of the five ratings measures. Figure 5.1 shows the various models I estimate where the controls are quite similar to those shown in Figure 4.1.

Figure 5.1: Controls Used for Different Models of UNC's Ratings

Model 1	Race/ethnicity, female, early or regular decision, alum, first generation, fee waiver, missing fee waiver, and year indicators
Model 2	Model 1 plus SAT math*; SAT verbal*; missing SAT times race/ethnicity; GPA*; missing GPA times race/ethnicity; percentile; percentile times non-standard rank type, missing percentile times year; race/ethnicity; non-standard rank type; non-standard rank type times race/ethnicity; indicators for different ways of imputing SAT * indicates variable was z-scored, GPA is only for those on a 4pt scale
Model 3	Model 2 plus indicators for UNC for all UNC ratings besides the rating that is the dependent variable
Model 4	Model 3 plus intended college major; female interacted with race/ethnicity; first-generation interacted with race/ethnicity
Model 5	Same as model 4 but only for the set of students from high schools that had a minimum number of applications and admits
Model 6	Model 5 plus high school fixed effects
Model 7	Same as model 6 but only for the set of students with census tract data who had a minimum number of applications and admits *Note this is only for the in-state models

Table A.5.1 displays the results for in-state applicants. Both the program and performance ratings show large racial differences that generally disappear once all the controls are added.[43] Like the program and

[43] The one exception is for Asian-American applicants, who have a positive and significant coefficient in the program rating. That positive sign in the program rating regression is indicative of Asian-American applicants taking

performance ratings, the activity and essay ratings show large racial differences which generally disappear once controls are added. The one exception is the extracurricular activity rating for Asian-American and Hispanic applicants, which are negative and significant even after including all the controls. In other words, even after all controls are added, Asian-American and Hispanic applicants tend to receive lower extracurricular activity ratings than would be suggested by their observed characteristics.

But the most striking result is for the personal rating. Here the coefficient on African American starts out at effectively zero but then becomes positive and significant as more controls are added. That the coefficient increases in magnitude as more controls are added implies that African-American applicants have observed characteristics that are associated with lower personal quality ratings. This further implies that African-American applicants are receiving a preference on the personal rating, given my assumption that unobservables run in the same direction as observables.[44] This assumption is bolstered by the fact that the coefficient increases continuously as more controls are added, suggesting that controlling for additional factors (*i.e.*, the unobservables) would behave

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relatively more AP/IB/Honors classes. The fact that Asian-American applicants take more AP classes negatively affects their performance rating, which is based on unweighted grades.

[44] Rosenberg Depo. 250:13-251:5 (explaining that race can play a factor in the personal quality rating); Perkins Depo. 40:3-43:10.-

similarly.[45]

The same racial differences with respect to the personal-quality rating exist in the out-of-state dataset, except that the preference is more pronounced. As shown in Table A.5.2, the coefficient on African American starts out positive and significant and increases in magnitude as more controls are added.[46] The same is true for Hispanic applicants. By controlling for a variable that incorporates a racial preference, I am likely underestimating the role of race/ethnicity in admissions decisions—particularly in the out-of-state dataset.[47]

[45] A similar pattern is also seen for Hispanic applicants. Though the differences across specifications are not as large, the coefficient on Hispanic becomes more and more positive as controls are added, implying a preference in favor of Hispanics on the personal quality rating.

[46] Recall that the gap between the observed characteristics of African-American applicants and non-URM applicants is larger in the out-of-state dataset than in the in-state dataset. This is indicative of a preference of larger magnitude for out-of-state African-American applicants on the personal quality rating.

[47] That racial preferences are more pronounced in the out-of-state dataset is further confirmed by the essay rating. For this rating, the coefficient on African American begins large and negative; once all controls are added, the coefficient on African American becomes positive and significant. Again, this suggests that racial preferences affect the scoring of the essay rating, in favor of African-American applicants.

Dated: January 12, 2018

s/ Peter S. Arcidiacono
Peter S. Arcidiacono

Appendix A

Appendix A

This appendix provides more details regarding data creation and different cuts of the summary statistics.

1. Sample selection

This section describes how I identified the populations to be analyzed. To start I removed withdrawn applications and those that were incomplete. A total of 2,840 (4.4%) in-state applications and 7,772 (5.7%) out-of-state applications fell into this category (Tables A.2.1 and A.2.2). The percentage of applications removed due to this restriction was fairly consistent across the application years I analyzed, ranging from 3.5% to 5.7% among in-state applicants and 4.5% to 6.4% percent among out-of-state applicants.

The next restriction I applied to the pool of applicants was to remove those that had any rating (program, performance, activity, essay, personal quality) of zero. Less than one percent of applicants and admits fell into this category—0.5% (0.7%) of in-state applicants (admits) and 0.3% (0.3%) of out-of-state applicants (admits) again, with the percentage varying relatively little across the application years.

I then removed applications that fell into the special categories. As noted in the main text, these special categories include applicants in special recruiting categories where the admit rate was more than 97% and where the observations were somewhat evenly distributed across years. More than 30 special categories

exist, including athletes.[48] I removed 4,590 (7.0%) in-state applicants and 4,273 (3.2%) out-of-state applicants with this restriction. Of these 4,577 of the in-state applicants were admitted as were 4,249 of the out-of-state applicants. The percentage of in-state applicants that fell into the special category ranged from 6.0% to 9.0% over the 2016 to 2021 admission years. The percentage of out-state applicants that fell into the special category ranged from 2.7% to 3.6% over this time period. Relatively few (153; 0.2%) in-state applicants were removed because they were foreign applicants. The percentage of foreign applicants among the out-of-state applicant pool was much larger, as one might expect. I removed 17,230 foreign out-of-state applicants, representing 12.7% of the total number of out-of-state applicants. This percentage ranged from 11.4% to 13.8% over the 2016 to 2021 period, notably with the percentage increasing in each year.

Finally, I restricted previous admits from the analysis sample. This restriction did not lead to any additional reduction in the analysis sample,

[48] The special categories I dropped are defined in UNC0079247, as follows: ACGN ("ACG (does not meet)"); ADVC ("Advanced courses"); ALAM ("Alamance"); CCAR ("Camp Carolina"); CSTE ("C-STEP"); DIST; DNSA; DNSC; DRMA ("Drama possible"); DRMF ("Drama final"); DTCH ("Durham Tech"); EPRG ("External program"); HMMB ("Special Opportunities maybe"); HMNM ("Special Opportunities invitee"); ISAR ("Innovative Scholars Access Rig"); JVB ("Basketball – JV Men"); LKLT ("Likely letter"); MCAR ("Morehead-Cain access rights"); MUSF ("Music final"); PGAL ("Pogue alternate"); PGAR ("Pogue access rights"); PGFN ("Pogue finalist"); PGNM ("Pogue nominee"); PGSF ("Pogue semi-finalist"); PGWN ("Pogue winner"); PTOS ("Priority OOS"); RBAL ("Robertson alternate"); RBFN ("Robertson finalist"); RBSF ("Robertson semi-finalist"); RBWN ("Robertson winner"); SBDF ("Sub-D final"); SCD1 ("Scholarship invitee day 1"); SCD2 ("Scholarship invitee day 2"); SCIE ("Science"); TRAD ("Trademark scholar"); ULFT ("Uplift"); and ATHL ("Athlete possible").

however, as the previous admits also fell into at least one of the restriction categories described above, for both the in-state and out-of-state applicants.

I obtained a final sample of 57,225 in-state applicants and 105,632 out-of-state applicants after imposing these sample restrictions.

2. Race and ethnicity definitions

I define race/ethnicity according to the field Ethnicity, created by UNC. This variable aggregates fields for whether the applicant checked that they were each of the following races/ethnicities:

- Caucasian (white)
- African American
- Hispanic / Latino
- Asian
- American Indian
- Hawaiian / Pacific Islander
- Missing (i.e. not populated on the Common Application)

Note that the above categories are not necessarily mutually exclusive. There exist a set of variables {CAUCA, AFRAM, HWPAC, AMIND, ASIAN, HSPLA} that are not mutually exclusive which indicate membership in any of the ethnic groups. The variable "Ethnicity" aggregates the data from each of the variables according to the following rules:

1. If the applicant lists African American as one of his races/ethnicities, then the applicant is coded as African American,

2. else if the applicant lists Native American, then the applicant is coded as Native American,
3. else if the applicant lists Hispanic, then the applicant is coded as Hispanic,
4. else if the applicant lists Asian, then the applicant is coded as Asian,
5. else if the applicant lists Hawaiian/Pacific Islander, then the applicant is coded as Hawaiian/Pacific Islander,
6. else if the applicant lists Caucasian, then the applicant is coded as white,
7. else if the applicant lists no race/ethnicity then the applicant is coded as missing.

For example, someone who lists that they are African American, Hispanic, and Caucasian would be coded as African American; someone who listed Hispanic and Asian would be coded as Hispanic.

3. Variable creation

Figures 4.1 and 5.1 document the variables included in each model. The following text describes how each of the variables was created.

<u>Admitted</u>: Admitted status is equal to the variable "Admit."

<u>Race/ethnicity</u>: Race/ethnicity is based on the variable "Ethnicity," with "1 CAUCA" coded as White, "2 HWPAC" coded as Hawaii / Pacific Islander, "3 ASIAN" coded as Asian, "4 AMIND" coded as American Indian, "5 HSPLA" coded as Hispanic, "6 AFRAM" coded as Black, and "-" or " " coded as missing.

Female: Female is based on the variable "Sex" with "F" coded as one, "M" coded as zero, and "U" coded as missing.

Early or regular decision: Early or regular decision is based on the variable "Notifcatn" with the value "ERLY" classified as early decision and value "REG" classified as regular decision.

Alumni: Alumni status is based on the variable "ALUM" with "ALUM" coded as one and "-" coded as zero.

First generation college: First generation college is based on the variable "fgcl."

Fee waiver: Fee waiver is based on the variable "PaymentType" and is equal to one if PaymentType is equal to "WAVR" and zero if PaymentType is equal to "CASH," "CHKM," "CRDT," "MORD," or "RETC." Fee waiver is also set equal to zero if PaymentType is equal to "-" or is missing.

Missing fee waiver: Missing fee waiver is based on the variable "PaymentType" and is equal to one if PaymentType is equal to "-" or missing, and is equal to zero otherwise.

Year indicators: Year indicators are based on the variable AdmitTerm. The AdmitTerm values are recoded as follows: 2109=2010, 2119=2011, 2129=2012, 2139=2013, 2149=2014, 2159=2015, 2169=2016, and 2179=2017. Year is equal to the recoded AdmitTerm value plus four (e.g., AdmitTerm = 2010 corresponds to year 2014).

SAT math: SAT math is based on the variables "MATH," "ACTCOMP," "ACTMATH," "ACTENGL," "ACTREAD," "ACTSCIENCE," and "SATTotal." For

applicants with SAT scores only, SAT math is equal to the applicant's SAT math score ("MATH"). For applicants with both SAT scores and ACT scores—based on variables "SATTotal" and "ACTCOMP"—SAT math is equal to the higher of two values: 1) the SAT math score or 2) the applicant's predicted SAT math score based on a regression of SAT math score on the components of the ACT, plus race and gender (defined above). For applicants with ACT scores only, the SAT math score is equal to the predicted value from the regression. One exception to this procedure exists for applicants in year 2021, for whom SAT math is equal to the variable "MSS" if it is nonzero. The applicant's SAT math score is then converted to a z-score by demeaning the variable and dividing by the standard deviation among all applicants.

SAT verbal: SAT verbal is based on the variables "READ," "ACTCOMP," "ACTMATH," "ACTENGL," "ACTREAD," "ACTSCIENCE," and "SATTotal," and is constructed using a procedure analogous to the one described above for the SAT math variable. For applicants in the year 2021, SAT verbal is equal to the variable "ERWS" if it is nonzero. The applicant's SAT verbal score is then converted to a z-score by demeaning the variable and dividing by the standard deviation among all applicants.

Missing SAT: SAT missing is equal to one if SAT score and ACT score data is not available to construct the SAT math and SAT verbal variables described above, and equal to zero otherwise.

SAT imputation indicators: A dichotomous SAT imputation indicator denotes if

an applicant has ACT test score data only (and, therefore, has SAT math and verbal scores based on the predicted value), or if an applicant has information on both tests and the predicted value is higher than the SAT score. Two additional dichotomous SAT imputation indicators denote: 1) whether an applicant is in year 2021, has ACT score data only, and has "HTOTL" equal to zero, and 2) whether an applicant is in year 2021 and has "HTOTL" not equal to zero.

GPA: GPA is based on the variables "ExtGPA" and "GPAType." GPA is set equal to "ExtGPA" if "GPAType" is equal to "4PT" and if "ExtGPA" is greater than or equal to one and less than or equal to 5.41; otherwise GPA is equal to zero. The applicant's GPA is then converted to a z-score by demeaning the variable and dividing by the standard deviation among all applicants.

Missing GPA: GPA missing is equal to one if GPA, described above, is equal to zero; otherwise GPA missing is equal to zero.

Percentile: Percentile is based on the variables "Percentile" and "ClassSize." Percentile is set equal to "Percentile" and then recoded to zero if ClassSize is equal to zero, 9999, or 99999, recoded to 100 if "Percentile" is equal to 689, and recoded to 0 if "Percentile" is equal to one.

Missing Percentile: Percentile missing is equal to one if "Percentile" is equal to zero or one, if "ClassSize" is equal to zero, 9999, or 99999, or if "RankType" is equal to "-"; otherwise percentile missing is equal to zero.

Non-standard rank type: Non-standard rank is based on the variable

"RankType" and is equal to one if "RankType" is equal to "NA," "OTH," or "-," and is equal to zero otherwise.

UNC program score: The UNC program score is based on variable "PROG."

UNC performance score: The UNC performance score is based on variable "PERF."

UNC activity score: The UNC activity score is based on variable "ACTIV."

UNC essay score: The UNC essay score is based on variable "ESSAYS."

UNC personal quality score: The UNC personal quality score is based on variable "PQ."

Intended college major: Intended major is based on the variable "APDescr1." Majors are grouped into seven categories: Education, Social Sciences, Arts & Humanities, Business and Economics, STEM, Other, and Undecided. The mappings can be found in program "UNCcleaner4N.do."

High school indicator: The high school indicator is based on the variable "ATP."

Census tract: Census tract is constructed from the first nine digits of the variable "13-Digit Block Group."

Table A.2.1: Sample Selection, In-State Applicants, 2016 - 2019

	2016			2017			2018			2019		
	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
Initial observations	5,028	10,169	10,169	5,100	10,091	10,091	5,198	9,861	9,861	5,387	10,360	10,360
Asian American												
Withdrawal, incomplete	0	583	9,586	0	536	9,555	0	429	9,432	0	366	9,994
	0.0%	5.7%		0.0%	5.3%		0.0%	4.4%		0.0%	3.5%	
Any rating zero	33	43	9,543	35	41	9,514	37	59	9,373	50	77	9,917
	0.7%	0.4%		0.7%	0.4%		0.7%	0.6%		0.9%	0.7%	
Any special	770	771	8,772	686	687	8,827	622	622	8,751	931	932	8,985
	15.3%	7.6%		13.5%	6.8%		12.0%	6.3%		17.3%	9.0%	
Foreign	18	33	8,739	14	23	8,804	15	29	8,722	12	21	8,964
	0.4%	0.3%		0.3%	0.2%		0.3%	0.3%		0.2%	0.2%	
Previous admit	0	0	8,739	0	0	8,804	0	0	8,722	0	0	8,964
	0.0%	0.0%		0.0%	0.0%		0.0%	0.0%		0.0%	0.0%	
Total removed	821	1,430	-------	735	1,287	-------	674	1,139	-------	993	1,396	-------
Total remaining	4,207	8,739	8,739	4,365	8,804	8,804	4,524	8,722	8,722	4,394	8,964	8,964

Notes:
[1] Percentages denote the number of observations cut as a percentage of the initial number of observations.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.2.1 (*continued*): Sample Selection, In-State Applicants, 2020 - 2021

	2020			2021			Total		
	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations
[1]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
Initial observations	5,760	11,744	11,744	5,842	12,898	12,898	32,315	65,123	65,123
Asian American									
Withdrawal, incomplete	0	438	11,306	0	488	12,410	0	2,840	62,283
	0.0%	3.7%		0.0%	3.8%		0.0%	4.4%	
Any rating zero	35	42	11,264	44	53	12,357	234	315	61,968
	0.6%	0.4%		0.8%	0.4%		0.7%	0.5%	
Any special	804	804	10,460	764	774	11,583	4,577	4,590	57,378
	14.0%	6.8%		13.1%	6.0%		14.2%	7.0%	
Foreign	11	28	10,432	12	19	11,564	82	153	57,225
	0.2%	0.2%		0.2%	0.1%		0.3%	0.2%	
Previous admit	0	0	10,432	0	0	11,564	0	0	57,225
	0.0%	0.0%		0.0%	0.0%		0.0%	0.0%	
Total removed	850	1,312	-------	820	1,334	-------	4,893	7,898	-------
Total remaining	4,910	10,432	10,432	5,022	11,564	11,564	27,422	57,225	57,225

Notes:
[1] Percentages denote the number of observations cut as a percentage of the initial number of observations.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.2.2: Sample Selection, Out-of-State Applicants, 2016 - 2019

	2016			2017			2018			2019		
	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations
[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
Initial observations	2,817	19,328	19,328	3,116	20,744	20,744	3,731	21,470	21,470	4,108	21,596	21,596
Asian American												
Withdrawal, incomplete	0	871	18,457	0	1,045	19,699	0	1,343	20,127	0	1,256	20,340
	0.0%	4.5%		0.0%	5.0%		0.0%	6.3%		0.0%	5.8%	
Any rating zero	9	28	18,429	9	28	19,671	19	145	19,982	15	121	20,219
	0.3%	0.1%		0.3%	0.1%		0.5%	0.7%		0.4%	0.6%	
Any special	669	671	17,758	740	745	18,926	719	721	19,261	725	727	19,492
	23.7%	3.5%		23.7%	3.6%		19.3%	3.4%		17.6%	3.4%	
Foreign	255	2,195	15,563	363	2,460	16,466	423	2,644	16,617	453	2,782	16,710
	9.1%	11.4%		11.6%	11.9%		11.3%	12.3%		11.0%	12.9%	
Previous admit	0	0	15,563	0	0	16,466	0	0	16,617	0	0	16,710
	0.0%	0.0%		0.0%	0.0%		0.0%	0.0%		0.0%	0.0%	
Total removed	933	3,765	-------	1,112	4,278	-------	1,161	4,853	-------	1,193	4,886	-------
Total remaining	1,884	15,563	15,563	2,004	16,466	16,466	2,570	16,617	16,617	2,915	16,710	16,710

Notes:
[1] Percentages denote the number of observations cut as a percentage of the initial number of observations.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.2.2 (*continued*): Sample Selection, Out-of-State Applicants, 2020 - 2021

	2020			2021			Total		
	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations	Admits	Applicants	Remaining observations
[1]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]
Initial observations	3,624	24,131	24,131	3,769	28,020	28,020	21,165	135,289	135,289
Asian American									
Withdrawal, incomplete	0	1,457	22,674	0	1,800	26,220	0	7,772	127,517
	0.0%	6.0%		0.0%	6.4%		0.0%	5.7%	
Any rating zero	12	22	22,652	6	38	26,182	70	382	127,135
	0.3%	0.1%		0.2%	0.1%		0.3%	0.3%	
Any special	647	648	22,004	749	761	25,421	4,249	4,273	122,862
	17.9%	2.7%		19.9%	2.7%		20.1%	3.2%	
Foreign	436	3,292	18,712	635	3,857	21,564	2,565	17,230	105,632
	12.0%	13.6%		16.8%	13.8%		12.1%	12.7%	
Previous admit	0	0	18,712	0	0	21,564	0	0	105,632
	0.0%	0.0%		0.0%	0.0%		0.0%	0.0%	
Total removed	1,095	5,419	-------	1,390	6,456	-------	6,884	29,657	-------
Total remaining	2,529	18,712	18,712	2,379	21,564	21,564	14,281	105,632	105,632

Notes:
[1] Percentages denote the number of observations cut as a percentage of the initial number of observations.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.4.1: Logit Estimates of In-State Admissions, 2016-2021

Variable	spec1	spec2	spec3	spec4	spec5	spec6	spec7
African American	-0.589	1.838	2.853	3.482	3.532	3.943	4.687
	(0.029)	(0.055)	(0.072)	(0.117)	(0.122)	(0.138)	(0.178)
Hispanic	-0.130	1.270	1.811	1.971	1.988	2.338	2.623
	(0.038)	(0.067)	(0.084)	(0.146)	(0.150)	(0.165)	(0.205)
Asian American	0.238	0.046	0.139	0.308	0.332	0.160	0.163
	(0.029)	(0.054)	(0.066)	(0.102)	(0.104)	(0.115)	(0.139)
female	0.104	0.294	0.115	0.193	0.211	0.192	0.177
	(0.018)	(0.030)	(0.038)	(0.045)	(0.046)	(0.051)	(0.064)
FGC	-0.305	0.518	0.805	1.014	1.015	1.102	1.251
	(0.024)	(0.038)	(0.049)	(0.061)	(0.063)	(0.071)	(0.092)
early	0.980	0.574	0.523	0.532	0.521	0.602	0.355
	(0.020)	(0.033)	(0.041)	(0.041)	(0.043)	(0.048)	(0.058)
alum	0.198	0.432	0.502	0.519	0.539	0.364	0.435
	(0.025)	(0.039)	(0.050)	(0.050)	(0.051)	(0.057)	(0.071)
waiver	-0.084	0.404	0.298	0.363	0.374	0.148	0.205
	(0.030)	(0.048)	(0.060)	(0.061)	(0.064)	(0.074)	(0.100)
female * race							
African American				-0.440	-0.464	-0.622	-0.644
				(0.120)	(0.125)	(0.138)	(0.179)
Hispanic				-0.122	-0.072	-0.167	-0.204
				(0.150)	(0.156)	(0.170)	(0.219)
Asian American				-0.258	-0.289	-0.374	-0.283
				(0.119)	(0.122)	(0.133)	(0.162)
FGC * race							
African American				-0.931	-0.898	-1.087	-1.404
				(0.122)	(0.127)	(0.143)	(0.190)
Hispanic				-0.300	-0.259	-0.510	-0.539
				(0.156)	(0.161)	(0.178)	(0.230)
Asian American				-0.132	-0.126	0.048	-0.093
				(0.140)	(0.143)	(0.159)	(0.200)
Academic variables		X	X	X	X	X	X
Ratings variables			X	X	X	X	X
Heterogeneity variables				X	X	X	X
HS fixed effects sample					X	X	X
HS fixed effects model						X	X
Census tract fixed effects							X
N	57,225	57,225	57,225	57,225	53,212	53,212	38,694
r2_p	0.056	0.565	0.715	0.716	0.712	0.750	0.768

Notes: The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx, UNC0379830.xlsx, UNC0379831.xlsx, UNC0379832.xlsx, UNC0379833.xlsx, UNC0379838.xlsx.

Table A.4.2: Logit Estimates of Out-of-State Admissions, 2016-2021

Variable	spec1	spec2	spec3	spec4	spec5	spec6
African American	0.866	4.681	5.852	6.059	6.151	7.090
	(0.033)	(0.077)	(0.094)	(0.124)	(0.154)	(0.187)
Hispanic	0.980	2.429	3.006	2.948	3.076	3.483
	(0.031)	(0.070)	(0.082)	(0.103)	(0.123)	(0.146)
Asian American	0.781	0.239	0.116	0.105	0.180	0.218
	(0.026)	(0.054)	(0.064)	(0.079)	(0.090)	(0.108)
female	-0.157	0.358	0.050	-0.052	-0.041	-0.080
	(0.019)	(0.025)	(0.030)	(0.040)	(0.045)	(0.053)
FGC	-0.172	0.863	1.325	1.814	1.966	2.428
	(0.033)	(0.043)	(0.052)	(0.074)	(0.092)	(0.110)
early	0.846	0.743	0.821	0.839	0.824	0.967
	(0.020)	(0.025)	(0.030)	(0.030)	(0.034)	(0.041)
alum	1.866	3.396	4.717	4.741	4.969	5.637
	(0.037)	(0.055)	(0.071)	(0.072)	(0.082)	(0.097)
waiver	-0.135	0.312	0.232	0.315	0.268	0.165
	(0.039)	(0.051)	(0.060)	(0.060)	(0.076)	(0.089)
female * race						
African American				0.089	0.124	0.060
				(0.107)	(0.130)	(0.150)
Hispanic				0.353	0.306	0.293
				(0.094)	(0.107)	(0.125)
Asian American				0.098	0.058	0.036
				(0.075)	(0.083)	(0.096)
FGC * race						
African American				-1.274	-1.164	-1.494
				(0.135)	(0.175)	(0.204)
Hispanic				-0.948	-0.883	-1.173
				(0.135)	(0.169)	(0.194)
Asian American				-0.492	-0.508	-0.663
				(0.129)	(0.151)	(0.175)
Academic variables		X	X	X	X	X
Ratings variables			X	X	X	X
Heterogeneity variables				X	X	X
HS fixed effects sample					X	X
HS fixed effects model						X
N	105,623	105,623	105,137	105,116	72,270	72,270
r2_p	0.073	0.416	0.584	0.586	0.582	0.644

Notes: The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.4.3: In-State Admissions Probabilities under Counterfactual Regimes

	Number of admits							Share of admits						
	2016	2017	2018	2019	2020	2021	Total	2016	2017	2018	2019	2020	2021	Total
Data														
White	3,021	3,003	3,134	3,043	3,308	3,356	18,865	71.8%	68.8%	69.3%	69.3%	67.4%	66.8%	68.8%
African American	383	373	405	373	429	411	2,374	9.1%	8.5%	9.0%	8.5%	8.7%	8.2%	8.7%
Hispanic	196	227	249	240	261	297	1,470	4.7%	5.2%	5.5%	5.5%	5.3%	5.9%	5.4%
Asian American	464	469	545	487	603	655	3,223	11.0%	10.7%	12.0%	11.1%	12.3%	13.0%	11.8%
Asian American	4,207	4,365	4,524	4,394	4,910	5,022	27,422							
No racial preferences														
White	3,247	3,175	3,341	3,210	3,483	3,518	19,974	77.2%	72.7%	73.9%	73.1%	70.9%	70.1%	72.8%
African American	219	241	248	240	267	295	1,510	5.2%	5.5%	5.5%	5.5%	5.4%	5.9%	5.5%
Hispanic	154	173	193	200	227	250	1,197	3.7%	4.0%	4.3%	4.6%	4.6%	5.0%	4.4%
Asian American	470	481	575	502	638	667	3,333	11.2%	11.0%	12.7%	11.4%	13.0%	13.3%	12.2%
No legacy preferences														
White	3,015	2,992	3,128	3,037	3,297	3,349	18,818	71.7%	68.5%	69.1%	69.1%	67.1%	66.7%	68.6%
African American	386	377	407	374	433	413	2,390	9.2%	8.6%	9.0%	8.5%	8.8%	8.2%	8.7%
Hispanic	197	230	250	241	264	299	1,481	4.7%	5.3%	5.5%	5.5%	5.4%	6.0%	5.4%
Asian American	466	473	547	489	607	657	3,239	11.1%	10.8%	12.1%	11.1%	12.4%	13.1%	11.8%
No racial or legacy preferences														
White	3,241	3,165	3,336	3,205	3,473	3,512	19,932	77.0%	72.5%	73.7%	72.9%	70.7%	69.9%	72.7%
African American	221	244	250	242	271	297	1,525	5.3%	5.6%	5.5%	5.5%	5.5%	5.9%	5.6%
Hispanic	155	175	195	202	230	252	1,209	3.7%	4.0%	4.3%	4.6%	4.7%	5.0%	4.4%
Asian American	472	485	577	504	642	669	3,349	11.2%	11.1%	12.8%	11.5%	13.1%	13.3%	12.2%

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.4.4: Out-of-State Admissions Probabilities under Counterfactual Regimes

	Number of admits							Share of admits						
	2016	2017	2018	2019	2020	2021	Total	2016	2017	2018	2019	2020	2021	Total
Data														
White	999	1,020	1,262	1,391	1,219	1,063	6,954	53.0%	50.9%	49.1%	47.7%	48.2%	44.7%	48.7%
African American	249	227	326	305	227	271	1,605	13.2%	11.3%	12.7%	10.5%	9.0%	11.4%	11.2%
Hispanic	242	239	310	361	339	330	1,821	12.8%	11.9%	12.1%	12.4%	13.4%	13.9%	12.8%
Asian American	293	323	478	582	485	537	2,698	15.6%	16.1%	18.6%	20.0%	19.2%	22.6%	18.9%
Asian American	1,884	2,004	2,570	2,915	2,529	2,379	14,281							
No racial preferences														
White	1,350	1,301	1,656	1,742	1,516	1,327	8,892	71.7%	64.9%	64.4%	59.8%	59.9%	55.8%	62.3%
African American	18	27	47	50	22	46	210	1.0%	1.3%	1.8%	1.7%	0.9%	1.9%	1.5%
Hispanic	64	104	128	150	134	162	742	3.4%	5.2%	5.0%	5.1%	5.3%	6.8%	5.2%
Asian American	385	337	562	698	590	670	3,242	20.4%	16.8%	21.9%	23.9%	23.3%	28.2%	22.7%
No legacy preferences														
White	968	982	1,214	1,350	1,166	998	6,678	51.4%	49.0%	47.2%	46.3%	46.1%	42.0%	46.8%
African American	257	234	337	312	236	282	1,658	13.6%	11.7%	13.1%	10.7%	9.3%	11.9%	11.6%
Hispanic	246	249	320	371	351	343	1,880	13.1%	12.4%	12.5%	12.7%	13.9%	14.4%	13.2%
Asian American	310	342	503	605	511	570	2,841	16.5%	17.1%	19.6%	20.8%	20.2%	24.0%	19.9%
No racial or legacy preferences														
White	1,328	1,272	1,623	1,711	1,476	1,275	8,685	70.5%	63.5%	63.2%	58.7%	58.4%	53.6%	60.8%
African American	19	27	49	50	21	46	212	1.0%	1.3%	1.9%	1.7%	0.8%	1.9%	1.5%
Hispanic	65	109	132	153	140	168	767	3.5%	5.4%	5.1%	5.2%	5.5%	7.1%	5.4%
Asian American	405	357	589	724	620	709	3,404	21.5%	17.8%	22.9%	24.8%	24.5%	29.8%	23.8%

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.4.5: Counterfactual Analysis Year-by-Year Logit Estimates of In-State Admissions, 2016-2021

Variable	2016	2017	2018	2019	2020	2021
African American	4.700	3.454	4.477	4.035	3.599	2.844
	(0.318)	(0.292)	(0.323)	(0.348)	(0.276)	(0.291)
Hispanic	2.552	2.942	3.224	1.985	1.209	1.699
	(0.392)	(0.419)	(0.405)	(0.400)	(0.308)	(0.355)
Asian American	0.574	0.408	0.178	0.225	0.154	0.517
	(0.267)	(0.284)	(0.259)	(0.290)	(0.234)	(0.254)
female	0.216	0.085	0.246	0.059	0.357	0.139
	(0.116)	(0.119)	(0.121)	(0.121)	(0.108)	(0.109)
FGC	1.088	1.512	1.128	1.249	0.638	1.057
	(0.149)	(0.156)	(0.162)	(0.165)	(0.150)	(0.150)
early	0.440	0.335	0.297	0.469	-0.013	2.007
	(0.098)	(0.103)	(0.111)	(0.113)	(0.100)	(0.121)
alum	0.497	0.804	0.463	0.431	0.656	0.444
	(0.129)	(0.136)	(0.133)	(0.131)	(0.118)	(0.121)
waiver	0.287	0.356	0.480	0.322	0.361	0.551
	(0.174)	(0.172)	(0.164)	(0.165)	(0.142)	(0.141)
female * race						
African American	-0.525	-0.257	-0.569	-0.593	-0.480	-0.471
	(0.315)	0.307	0.322	(0.346)	(0.280)	(0.301)
Hispanic	-0.801	0.278	-0.255	-0.455	-0.170	0.151
	(0.407)	0.431	0.413	(0.425)	(0.334)	(0.346)
Asian American	0.040	-0.176	-0.197	0.001	-0.577	-0.477
	(0.322)	0.324	0.307	(0.330)	(0.279)	(0.290)
FGC * race						
African American	-1.458	-1.047	-1.391	-0.812	-0.896	-0.754
	(0.313)	0.311	0.327	(0.347)	(0.297)	(0.309)
Hispanic	0.139	-1.480	-1.087	0.726	0.255	-0.562
	(0.427)	0.439	0.440	(0.446)	(0.356)	(0.358)
Asian American	-0.408	-0.228	-0.206	-0.198	0.134	-0.097
	(0.365)	0.364	0.351	(0.395)	(0.333)	(0.349)
N	8,627	8,457	8,491	8,712	10,344	10,361
r2_p	0.721	0.721	0.727	0.742	0.712	0.724

Notes: Regressions also control for academic variables, ratings variables, and heterogeneity variables. The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race.
Two 2016 admits with very low test scores (i.e., z-scores less than -2) and one admit from 2021 were excluded from the regression analysis to achieve convergence for these years.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.4.6: Counterfactual Analysis Year-by-Year Logit Estimates of Out-of-State Admissions, 2016-2021

Variable	2016	2017	2018	2019	2020	2021
African American	7.097	5.275	6.274	6.942	6.519	6.006
	(0.325)	(0.339)	(0.288)	(0.324)	(0.319)	(0.313)
Hispanic	3.921	2.769	2.637	3.402	3.235	2.708
	(0.297)	(0.263)	(0.250)	(0.263)	(0.262)	(0.251)
Asian American	0.008	0.481	0.253	-0.043	-0.094	-0.006
	(0.211)	(0.219)	(0.191)	(0.195)	(0.195)	(0.191)
female	0.059	-0.205	0.004	0.107	-0.089	-0.160
	(0.102)	(0.103)	(0.096)	(0.097)	(0.100)	(0.104)
FGC	1.758	2.006	1.224	2.262	1.348	2.701
	(0.191)	(0.187)	(0.188)	(0.176)	(0.197)	(0.185)
early	0.892	1.011	0.683	0.240	1.655	0.729
	(0.079)	(0.078)	(0.072)	(0.071)	(0.081)	(0.078)
alum	4.652	4.465	4.531	4.932	5.085	5.984
	(0.188)	(0.172)	(0.178)	(0.187)	(0.186)	(0.191)
waiver	-0.075	0.251	0.582	0.508	0.116	0.302
	(0.180)	(0.184)	(0.137)	(0.149)	(0.154)	(0.143)
female * race						
African American	0.296	0.954	0.127	-0.304	-0.235	-0.414
	(0.272)	0.292	0.252	(0.278)	(0.275)	(0.267)
Hispanic	0.554	0.171	0.718	0.362	0.166	0.228
	(0.270)	0.248	0.230	(0.235)	(0.228)	(0.226)
Asian American	0.170	0.130	-0.051	0.182	0.172	-0.047
	(0.207)	0.208	0.182	(0.183)	(0.186)	(0.180)
FGC * race						
African American	-1.141	-1.460	-0.716	-1.763	-1.117	-1.903
	(0.344)	0.342	0.330	(0.356)	(0.367)	(0.333)
Hispanic	-0.960	-0.809	-0.009	-1.011	-1.173	-2.006
	(0.361)	0.353	0.339	(0.315)	(0.354)	(0.349)
Asian American	-0.745	-0.580	-0.071	-0.625	-0.144	-0.725
	(0.354)	0.349	0.320	(0.308)	(0.334)	(0.302)
N	15,056	16,009	16,311	16,318	18,391	20,745
r2_p	0.572	0.580	0.582	0.614	0.616	0.622

Notes: Regressions also control for academic variables, ratings variables, and heterogeneity variables. The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race.
One 2016 admit with very low test scores (i.e., z-scores less than -2) was excluded from the regression analysis to achieve convergence in that year.

Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.5.1: Ratings Ordered Logit Estimates for In-State Applicants, 2016-2021

	Program						Performance						Activity					
Variable	spec1	spec2	spec3	spec4	spec5	spec6	spec1	spec2	spec3	spec4	spec5	spec6	spec1	spec2	spec3	spec4	spec5	spec6
African American	-0.488	0.373	0.281	0.249	0.237	0.063	-1.143	-0.316	-0.233	-0.147	-0.149	0.031	-0.557	-0.121	-0.190	-0.120	-0.126	-0.053
	(0.025)	(0.028)	(0.028)	(0.046)	(0.047)	(0.051)	(0.024)	(0.027)	(0.027)	(0.045)	(0.046)	(0.048)	(0.025)	(0.028)	(0.028)	(0.046)	(0.047)	(0.048)
Hispanic	-0.066	0.330	0.246	0.012	-0.007	0.100	-0.614	-0.248	-0.185	-0.102	-0.103	-0.062	-0.367	-0.156	-0.286	-0.177	-0.178	-0.172
	(0.032)	(0.036)	(0.036)	(0.060)	(0.061)	(0.064)	(0.032)	(0.035)	(0.035)	(0.061)	(0.062)	(0.063)	(0.033)	(0.036)	(0.036)	(0.062)	(0.063)	(0.063)
Asian American	0.842	0.728	0.581	0.608	0.608	0.783	-0.276	-0.600	-0.401	-0.502	-0.511	-0.392	-0.105	-0.260	-0.321	-0.189	-0.199	-0.213
	(0.025)	(0.029)	(0.029)	(0.044)	(0.045)	(0.048)	(0.025)	(0.028)	(0.028)	(0.043)	(0.044)	(0.046)	(0.026)	(0.029)	(0.029)	(0.044)	(0.045)	(0.046)
Female	-0.028	-0.049	0.016	0.018	0.004	0.044	0.413	0.299	0.288	0.305	0.293	0.330	0.130	0.163	0.104	0.152	0.153	0.154
	(0.015)	(0.016)	(0.016)	(0.020)	(0.020)	(0.021)	(0.015)	(0.016)	(0.017)	(0.020)	(0.020)	(0.021)	(0.016)	(0.017)	(0.017)	(0.021)	(0.021)	(0.021)
First Generation	-0.302	-0.039	0.039	0.001	-0.014	-0.062	-0.146	0.141	0.147	0.137	0.129	-0.072	-0.543	-0.392	-0.389	-0.355	-0.362	-0.369
	(0.020)	(0.021)	(0.021)	(0.027)	(0.028)	(0.030)	(0.020)	(0.021)	(0.021)	(0.027)	(0.028)	(0.029)	(0.021)	(0.021)	(0.021)	(0.028)	(0.028)	(0.029)
Regular Admission	-0.616	-0.121	-0.152	-0.155	-0.159	-0.219	-0.776	-0.067	-0.112	-0.113	-0.120	-0.100	-0.454	-0.204	-0.186	-0.179	-0.178	-0.180
	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.020)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)
Legacy	0.053	0.086	0.056	0.059	0.060	-0.035	-0.055	-0.044	-0.029	-0.023	-0.022	-0.057	0.224	0.223	0.195	0.189	0.186	0.137
	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.023)	(0.021)	(0.021)	(0.022)	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)
Waiver	0.067	0.296	0.339	0.324	0.337	0.006	-0.012	0.120	0.216	0.221	0.245	0.165	-0.203	-0.108	-0.202	-0.194	-0.189	-0.168
	(0.026)	(0.027)	(0.027)	(0.027)	(0.028)	(0.031)	(0.025)	(0.026)	(0.026)	(0.026)	(0.027)	(0.029)	(0.026)	(0.026)	(0.026)	(0.027)	(0.027)	(0.029)
female * race																		
African American				0.077	0.095	-0.022				-0.106	-0.105	-0.130				-0.160	-0.147	-0.128
				(0.049)	(0.051)	(0.054)				(0.048)	(0.050)	(0.051)				(0.049)	(0.050)	(0.051)
Hispanic				0.104	0.105	0.041				-0.092	-0.105	-0.110				-0.120	-0.136	-0.133
				(0.066)	(0.067)	(0.071)				(0.065)	(0.066)	(0.068)				(0.067)	(0.068)	(0.068)
Asian American				-0.063	-0.056	-0.138				0.072	0.077	0.040				-0.046	-0.037	-0.039
				(0.052)	(0.053)	(0.055)				(0.051)	(0.052)	(0.053)				(0.052)	(0.052)	(0.053)
FGC * race																		
African American				-0.052	-0.033	-0.070				-0.057	-0.039	0.100				0.103	0.094	0.097
				(0.052)	(0.053)	(0.057)				(0.050)	(0.052)	(0.054)				(0.051)	(0.052)	(0.053)
Hispanic				0.380	0.412	0.277				-0.064	-0.039	0.109				-0.058	-0.042	0.015
				(0.069)	(0.070)	(0.075)				(0.068)	(0.069)	(0.071)				(0.070)	(0.071)	(0.072)
Asian American				0.041	0.071	-0.067				0.172	0.187	0.344				-0.289	-0.274	-0.215
				(0.062)	(0.063)	(0.067)				(0.061)	(0.062)	(0.064)				(0.062)	(0.063)	(0.064)
Academic variables		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X
Ratings variables			X	X	X	X			X	X	X	X			X	X	X	X
Heterogeneity variables				X	X	X				X	X	X				X	X	X
HS fixed effects sample					X	X					X	X					X	X
HS fixed effects model						X						X						X
N	57,225	57,225	57,225	57,225	55,294	55,294	57,225	57,225	57,225	57,225	55,294	55,294	57,225	57,225	57,225	57,225	55,294	55,294
r2_p	0.019	0.098	0.131	0.132	0.136	0.247	0.028	0.219	0.25	0.25	0.258	0.315	0.023	0.049	0.081	0.082	0.083	0.095

Notes: The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race. r2_p denotes pseudo-R-squared, a measure of model fit. Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.5.1 (*continued*): Ratings Ordered Logit Estimates for In-State Applicants, 2016-2021

	Essay						Personal Quality					
Variable	spec1	spec2	spec3	spec4	spec5	spec6	spec1	spec2	spec3	spec4	spec5	spec6
African American	-0.710	-0.022	-0.086	-0.044	-0.043	-0.016	0.009	0.416	0.480	0.628	0.636	0.652
	(0.034)	(0.038)	(0.039)	(0.063)	(0.065)	(0.067)	(0.034)	(0.039)	(0.041)	(0.067)	(0.069)	(0.071)
Hispanic	-0.084	0.222	0.151	-0.005	-0.016	-0.038	0.279	0.515	0.542	0.447	0.442	0.469
	(0.045)	(0.050)	(0.052)	(0.090)	(0.091)	(0.092)	(0.043)	(0.048)	(0.050)	(0.088)	(0.089)	(0.090)
Asian American	0.210	0.113	0.165	-0.025	-0.027	-0.093	0.124	0.052	0.091	0.063	0.090	0.047
	(0.036)	(0.040)	(0.042)	(0.064)	(0.064)	(0.067)	(0.035)	(0.040)	(0.043)	(0.066)	(0.066)	(0.069)
Female	0.216	0.342	0.283	0.209	0.210	0.147	0.109	0.137	0.002	0.020	0.022	0.002
	(0.022)	(0.023)	(0.024)	(0.030)	(0.031)	(0.031)	(0.022)	(0.023)	(0.025)	(0.030)	(0.031)	(0.032)
First Generation	-0.771	-0.399	-0.363	-0.368	-0.351	-0.201	-0.064	0.160	0.356	0.312	0.319	0.328
	(0.029)	(0.030)	(0.031)	(0.040)	(0.041)	(0.043)	(0.029)	(0.030)	(0.031)	(0.041)	(0.042)	(0.044)
Regular Admission	-0.249	-0.002	0.084	0.072	0.074	0.079	-0.298	-0.113	-0.012	-0.016	-0.018	-0.013
	(0.024)	(0.025)	(0.026)	(0.026)	(0.027)	(0.027)	(0.025)	(0.026)	(0.027)	(0.027)	(0.028)	(0.029)
Legacy	0.189	0.147	0.079	0.067	0.069	0.030	0.125	0.100	0.025	0.021	0.020	-0.007
	(0.030)	(0.031)	(0.032)	(0.032)	(0.033)	(0.034)	(0.030)	(0.030)	(0.032)	(0.032)	(0.032)	(0.033)
Waiver	-0.388	-0.120	-0.210	-0.216	-0.228	-0.146	0.393	0.536	0.610	0.602	0.590	0.576
	(0.035)	(0.035)	(0.036)	(0.037)	(0.038)	(0.040)	(0.034)	(0.035)	(0.036)	(0.037)	(0.038)	(0.040)
female * race												
African American				-0.025	-0.022	-0.039				-0.205	-0.195	-0.208
				(0.067)	(0.068)	(0.070)				(0.070)	(0.072)	(0.073)
Hispanic				0.216	0.227	0.230				-0.009	-0.005	-0.011
				(0.094)	(0.096)	(0.097)				(0.092)	(0.094)	(0.095)
Asian American				0.368	0.375	0.382				0.004	-0.021	0.004
				(0.073)	(0.074)	(0.075)				(0.075)	(0.076)	(0.077)
FGC * race												
African American				-0.012	0.003	-0.107				0.019	0.002	-0.013
				(0.070)	(0.072)	(0.073)				(0.074)	(0.076)	(0.078)
Hispanic				0.074	0.087	-0.019				0.220	0.207	0.172
				(0.098)	(0.100)	(0.102)				(0.096)	(0.098)	(0.100)
Asian American				-0.028	-0.046	-0.124				0.119	0.099	0.126
				(0.087)	(0.089)	(0.091)				(0.090)	(0.091)	(0.094)
Academic variables		X	X	X	X	X		X	X	X	X	X
Ratings variables			X	X	X	X			X	X	X	X
Heterogeneity variables				X	X	X				X	X	X
HS fixed effects sample					X	X					X	X
HS fixed effects model						X						X
N	57,225	57,225	57,225	57,225	55,294	55,294	57,225	57,225	57,225	57,225	55,294	55,294
r2_p	0.042	0.109	0.178	0.18	0.179	0.195	0.031	0.059	0.151	0.152	0.151	0.163

Notes: The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race. Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.5.2: Ratings Ordered Logit Estimates for Out-of-State Applicants, 2016-2021

	Program						Performance						Activity					
Variable	spec1	spec2	spec3	spec4	spec5	spec6	spec1	spec2	spec3	spec4	spec5	spec6	spec1	spec2	spec3	spec4	spec5	spec6
African American	-0.536	0.600	0.573	0.443	0.434	0.236	-1.317	-0.187	-0.215	-0.220	-0.128	0.161	-0.605	0.008	-0.187	-0.097	-0.026	0.028
	(0.021)	(0.031)	(0.031)	(0.044)	(0.060)	(0.067)	(0.021)	(0.031)	(0.031)	(0.044)	(0.059)	(0.063)	(0.021)	(0.031)	(0.032)	(0.045)	(0.061)	(0.065)
Hispanic	0.261	0.580	0.554	0.375	0.368	0.144	-0.508	-0.421	-0.427	-0.449	-0.538	-0.188	-0.194	-0.027	-0.163	-0.138	-0.193	-0.172
	(0.021)	(0.034)	(0.034)	(0.045)	(0.058)	(0.065)	(0.020)	(0.033)	(0.033)	(0.044)	(0.056)	(0.059)	(0.021)	(0.034)	(0.034)	(0.045)	(0.057)	(0.060)
Asian American	0.831	0.771	0.769	0.808	0.831	0.928	-0.142	-0.453	-0.416	-0.434	-0.433	-0.539	0.140	-0.042	-0.093	0.000	0.042	0.010
	(0.016)	(0.028)	(0.028)	(0.035)	(0.044)	(0.049)	(0.016)	(0.027)	(0.027)	(0.034)	(0.041)	(0.044)	(0.016)	(0.027)	(0.028)	(0.035)	(0.042)	(0.045)
Female	-0.022	0.082	0.068	0.046	-0.006	0.061	0.435	0.583	0.556	0.552	0.576	0.595	0.069	0.205	0.090	0.135	0.162	0.161
	(0.011)	(0.012)	(0.012)	(0.015)	(0.019)	(0.020)	(0.011)	(0.012)	(0.012)	(0.015)	(0.019)	(0.020)	(0.011)	(0.012)	(0.012)	(0.016)	(0.019)	(0.020)
First Generation	-0.339	-0.026	-0.005	-0.063	0.001	-0.033	-0.344	-0.070	-0.057	-0.096	-0.158	-0.103	-0.573	-0.297	-0.324	-0.282	-0.270	-0.281
	(0.018)	(0.019)	(0.019)	(0.026)	(0.038)	(0.040)	(0.018)	(0.019)	(0.019)	(0.026)	(0.037)	(0.039)	(0.019)	(0.019)	(0.019)	(0.027)	(0.038)	(0.039)
Regular Admission	-0.249	-0.004	0.005	-0.002	-0.008	-0.019	-0.466	-0.201	-0.182	-0.182	-0.208	-0.240	-0.291	-0.127	-0.097	-0.093	-0.108	-0.113
	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.015)	(0.011)	(0.012)	(0.012)	(0.012)	(0.014)	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.015)
Legacy	-0.104	0.067	0.039	0.042	0.053	-0.062	-0.323	-0.133	-0.155	-0.144	-0.173	-0.140	0.046	0.108	0.061	0.062	0.029	0.039
	(0.030)	(0.031)	(0.031)	(0.031)	(0.035)	(0.037)	(0.030)	(0.031)	(0.031)	(0.031)	(0.035)	(0.037)	(0.031)	(0.031)	(0.032)	(0.032)	(0.036)	(0.037)
Waiver	0.006	0.158	0.136	0.116	0.238	0.106	-0.111	-0.100	-0.119	-0.122	-0.141	0.005	-0.184	-0.047	-0.195	-0.183	-0.234	-0.189
	(0.023)	(0.023)	(0.023)	(0.023)	(0.034)	(0.038)	(0.022)	(0.023)	(0.023)	(0.023)	(0.033)	(0.035)	(0.023)	(0.023)	(0.023)	(0.024)	(0.034)	(0.036)
female * race																		
African American				0.162	0.198	0.219				-0.058	-0.070	-0.079				-0.094	-0.090	-0.112
				(0.042)	(0.056)	(0.059)				(0.042)	(0.055)	(0.057)				(0.043)	(0.057)	(0.058)
Hispanic				0.169	0.203	0.127				0.086	0.073	0.077				-0.040	-0.046	-0.044
				(0.042)	(0.052)	(0.057)				(0.041)	(0.051)	(0.053)				(0.042)	(0.052)	(0.054)
Asian American				-0.090	-0.056	-0.060				-0.040	-0.047	-0.033				-0.107	-0.112	-0.112
				(0.033)	(0.038)	(0.041)				(0.032)	(0.037)	(0.039)				(0.033)	(0.039)	(0.040)
FGC * race																		
African American				0.058	0.045	-0.012				0.097	0.203	0.218				-0.075	-0.129	-0.104
				(0.050)	(0.073)	(0.078)				(0.049)	(0.072)	(0.075)				(0.051)	(0.074)	(0.076)
Hispanic				0.271	0.324	0.177				-0.100	0.027	0.050				-0.003	0.014	0.051
				(0.055)	(0.079)	(0.085)				(0.053)	(0.075)	(0.078)				(0.055)	(0.077)	(0.079)
Asian American				0.028	0.050	0.043				0.148	0.155	0.158				-0.119	-0.183	-0.164
				(0.050)	(0.067)	(0.072)				(0.050)	(0.066)	(0.069)				(0.051)	(0.067)	(0.069)
Academic variables		X	X	X	X	X		X	X	X	X	X		X	X	X	X	X
Ratings variables			X	X	X	X			X	X	X	X			X	X	X	X
Heterogeneity variables				X	X	X				X	X	X				X	X	X
HS fixed effects sample					X	X					X	X					X	X
HS fixed effects model						X						X						X
N	105,631	105,631	105,631	105,631	72,357	72,357	105,631	105,631	105,631	105,631	72,357	72,357	105,631	105,631	105,631	105,631	72,357	72,357
r2_p	0.015	0.085	0.089	0.089	0.095	0.252	0.024	0.152	0.156	0.158	0.15	0.228	0.019	0.048	0.09	0.091	0.09	0.11

Notes: The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score, performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race. r2_p denotes pseudo-R-squared, a measure of model fit.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.5.2 (*continued*): Ratings Ordered Logit Estimates for Out-of-State Applicants, 2016-2021

	Essay						Personal Quality					
Variable	spec1	spec2	spec3	spec4	spec5	spec6	spec1	spec2	spec3	spec4	spec5	spec6
African American	-0.501	0.312	0.141	0.199	0.352	0.490	0.150	0.792	0.760	0.812	0.922	0.914
	(0.032)	(0.046)	(0.047)	(0.067)	(0.091)	(0.096)	(0.028)	(0.043)	(0.045)	(0.064)	(0.085)	(0.091)
Hispanic	0.003	0.272	0.154	0.057	0.117	0.183	0.295	0.545	0.549	0.574	0.568	0.541
	(0.029)	(0.049)	(0.051)	(0.067)	(0.086)	(0.092)	(0.026)	(0.044)	(0.047)	(0.061)	(0.078)	(0.084)
Asian American	0.438	0.264	0.272	0.177	0.175	0.178	0.199	0.060	-0.044	-0.071	-0.067	-0.005
	(0.021)	(0.037)	(0.039)	(0.049)	(0.060)	(0.065)	(0.021)	(0.037)	(0.040)	(0.049)	(0.060)	(0.064)
Female	0.203	0.399	0.327	0.257	0.257	0.234	0.028	0.159	-0.013	-0.015	0.001	-0.007
	(0.016)	(0.017)	(0.018)	(0.024)	(0.028)	(0.030)	(0.015)	(0.016)	(0.018)	(0.023)	(0.028)	(0.030)
First Generation	-0.646	-0.164	-0.142	-0.132	-0.041	0.033	-0.137	0.178	0.325	0.282	0.254	0.312
	(0.028)	(0.028)	(0.029)	(0.041)	(0.059)	(0.061)	(0.025)	(0.026)	(0.028)	(0.040)	(0.057)	(0.059)
Regular Admission	-0.291	-0.092	-0.029	-0.038	-0.081	-0.085	-0.258	-0.100	-0.033	-0.038	-0.050	-0.019
	(0.016)	(0.017)	(0.017)	(0.017)	(0.021)	(0.022)	(0.015)	(0.016)	(0.017)	(0.017)	(0.020)	(0.022)
Legacy	0.142	0.176	0.126	0.104	0.136	0.138	0.174	0.217	0.176	0.170	0.215	0.170
	(0.042)	(0.043)	(0.045)	(0.045)	(0.051)	(0.054)	(0.040)	(0.041)	(0.044)	(0.044)	(0.050)	(0.052)
Waiver	-0.145	0.112	-0.004	-0.004	0.041	0.024	0.419	0.606	0.652	0.640	0.664	0.649
	(0.033)	(0.033)	(0.034)	(0.034)	(0.049)	(0.051)	(0.028)	(0.029)	(0.031)	(0.031)	(0.044)	(0.047)
female * race												
African American				0.029	-0.020	-0.040				-0.054	-0.049	-0.033
				(0.063)	(0.084)	(0.087)				(0.060)	(0.077)	(0.080)
Hispanic				0.135	0.138	0.102				-0.118	-0.126	-0.145
				(0.063)	(0.077)	(0.081)				(0.057)	(0.070)	(0.074)
Asian American				0.144	0.177	0.190				0.026	-0.001	-0.004
				(0.046)	(0.054)	(0.056)				(0.046)	(0.054)	(0.056)
FGC * race												
African American				-0.187	-0.249	-0.250				-0.003	-0.036	-0.063
				(0.074)	(0.112)	(0.116)				(0.071)	(0.103)	(0.108)
Hispanic				0.042	0.035	0.017				0.190	0.064	0.001
				(0.082)	(0.116)	(0.121)				(0.074)	(0.105)	(0.110)
Asian American				0.150	0.094	0.073				0.114	0.125	0.084
				(0.076)	(0.099)	(0.103)				(0.072)	(0.095)	(0.099)
Academic variables		X	X	X	X	X		X	X	X	X	X
Ratings variables			X	X	X	X			X	X	X	X
Heterogeneity variables				X	X	X				X	X	X
HS fixed effects sample					X	X					X	X
HS fixed effects model						X						X
N	105,631	105,631	105,631	105,631	72,357	72,357	105,631	105,631	105,631	105,631	72,357	72,357
r2_p	0.023	0.096	0.175	0.177	0.167	0.194	0.034	0.073	0.185	0.186	0.187	0.213

Notes: The academic variables include SAT math and verbal scores (entered as z-scores), percentile, rank, GPA, percentile*rank, and GPA*race, plus controls for missing variables. The ratings variables include program score,

performance, activities, essay scores, and personal quality. The heterogeneity variables include intended major, missing intended major, female*race, and FGC*race. r2_p denotes pseudo-R-squared, a measure of model fit.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Table A.5.3: Index Values in Standard Deviation Units for Model Specification #4, by Race

	Program	Performance	Activities	Essay	Personal Quality
In-State					
African American	-0.735	-0.785	-0.795	-0.869	-0.380
Hispanic	-0.343	-0.433	-0.477	-0.528	-0.144
Asian American	0.283	-0.078	0.042	-0.091	0.008
Asian American					
African American	-1.103	-1.064	-0.723	-0.766	-0.457
Hispanic	-0.242	-0.235	-0.189	-0.240	-0.106
Asian American	0.170	0.065	0.157	0.076	0.177

Notes: Model Specification #4 controls for applicant demographic and academic characteristics and ratings.
Sources: MainDataA.csv, MainDataB.csv, MainDataC.csv, MainDataD.csv, UNC0379828.xlsx, UNC0379829.xlsx.

Appendix B

Peter Arcidiacono
March 2017

Address

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Employment and Affiliations

Duke University
- Full Professor, July 2010-present
- Associate Professor (with tenure), July 2006-June 2010
- Assistant Professor, September 1999-June, 2006

National Bureau of Economic Research
- Research Associate, 2008-present

IZA Research Fellow, September 2015-present

Education

Ph.D. in Economics, University of Wisconsin, Madison, WI, August 1999.

B.S. in Economics, Willamette University, Salem, OR, May 1993.

Published and Forthcoming Articles (*=not refereed)

"Finite Mixture Distributions, Sequential Likelihood, and the EM Algorithm," (joint with John B. Jones at SUNY-Albany), *Econometrica,* Vol. 71, No.3 (May, 2003), 933-946

"The Dynamic Implications of Search Discrimination," *Journal of Public Economics,* Vol. 87, Nos.7-8 (August, 2003), 1681-1707

"Paying to Queue: A Theory of Locational Differences in Nonunion Wages," (joint with Tom Ahn), *Journal of Urban Economics,* Vol. 55, No. 3 (May 2004), 564-579

"Ability Sorting and the Returns to College Major," *Journal of Econometrics*, Vol. 121, Nos. 1-2 (August, 2004), 343-375

"Peer Effects in Medical School," (joint with Sean Nicholson) *Journal of Public Economics,* Vol. 89, Nos. 2-3 (February, 2005), 327-350

"Do People Value Racial Diversity? Evidence From Nielsen Ratings" (joint with Eric Aldrich and Jacob Vigdor), *Topics in Economic Analysis and Policy*, Vol. 5, No. 1 (2005), Article 4

“Affirmative Action in Higher Education: How do Admission and Financial Aid Rules Affect Future Earnings?” *Econometrica,* Vol. 73, No. 5 (September, 2005), 1477-1524

“Games and Discrimination: Lessons from the Weakest Link,” (joint with Kate Antonovics and Randy Walsh), *Journal of Human Resources,* Vol. 40, No.4 (Fall, 2005)

“Living Rationally Under the Volcano? An Empirical Analysis of Heavy Drinking and Smoking,” (joint with Holger Sieg at Carnegie Mellon and Frank Sloan) *International Economic Review,* Vol. 48, No. 1 (February 2007)

“The Economic Returns to an MBA,” (joint with Jane Cooley and Andrew Hussey) *International Economic Review,* Vol. 49, No.3 (August 2008), 873-899

“The Effects of Gender Interactions in the Lab and in the Field,” (joint with Kate Antonovics and Randy Walsh) *Review of Economics and Statistics,* Vol. 91, No. 1 (February 2009)

“Explaining Cross-Racial Differences in Teenage Labor Force Participation: Results from a General Equilibrium Search Model” (joint with Tom Ahn, Alvin Murphy and Omari Swinton) *Journal of Econometrics,* Vol. 156, No. 2 (May 2010)

“Does The River Spill Over? Estimating the Economic Returns to Attending a Racially Diverse College” (joint with Jacob Vigdor) *Economic Inquiry,* Vol. 47, No. 3 (July 2010)

“The Distributional Effects of Minimum Wage Increases when Both Labor Supply and Labor Demand are Endogenous” (joint with Tom Ahn and Walter Wessels) *Journal of Business and Economic Statistics,* Vol. 29, No. 1 (January 2011), 12-23

“Beyond Signaling and Human Capital: Education and the Revelation of Ability” (joint with Pat Bayer and Aurel Hizmo) *AEJ: Applied Economics,* Vol. 2, No. 4 (October 2010), 76-104

“Representation versus Assimilation: How do Preferences in College Admissions Affect Social Interactions?” (joint with Shakeeb Khan and Jacob Vigdor) *Journal of Public Economics*, Vol. 95, No. 1-2 (February 2011), 1-15.

“Practical Methods for Estimation of Dynamic Discrete Choice Models” (joint with Paul Ellickson) *Annual Review of Economics Volume 3,* September 2011, 363-394

“Conditional Choice Probability Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity” (joint with Bob Miller) *Econometrica,* Vol. 7, No. 6 (November 2011), 1823-1868 *(formerly titled “CCP Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity”)*

“Does Affirmative Action Lead to Mismatch? A New Test and Evidence” (joint with Esteban Aucejo, Hanming Fang, and Ken Spenner) *Quantitative Economics* Vol. 2, No. 3 (November 2011), 303-333

“Modeling College Major Choice using Elicited Measures of Expectations and Counterfactuals” (joint with Joe Hotz and Songman Kang) *Journal of Econometrics* Vol. 166, No. 1 (January 2012), 3-16

“Habit Persistence and Teen Sex: Could Increased Access to Contraception have Unintended Consequences for Teen Pregnancies?” (joint with Ahmed Khwaja and Lijing Ouyang) *Journal of Business and Economic Statistics,* Vol. 30, No. 2 (November 2012), 312-325.

“What Happens After Enrollment? An Analysis of the Time Path of Racial Differences in GPA and Major Choice” (joint with Esteban Aucejo and Ken Spenner) *IZA: Journal of Labor Economics,* Vol. 1, No. 5 (October 2012)

“Estimating Spillovers using Panel Data, with an Application to the Classroom” (joint with Jennifer Foster, Natalie Goodpaster, and Josh Kinsler) *Quantitative Economics,* Vol. 3, No. 3 (November 2012), 421-470.

“Pharmaceutical Followers” (joint with Paul Ellickson, Peter Landry, and David Ridley) *International Journal of Industrial Organization,* Vol. 3, No. 5 (September 2013), 538-553 *Winner of the 2014 IJIO Best Paper Award*

“Racial Segregation Patterns in Selective Universities” (joint with Esteban Aucejo, Andrew Hussey, and Ken Spenner) *Journal of Law Economics,* Vol. 56 (November 2013)

“Approximating High Dimensional Dynamic Models: Sieve Value Function Iteration” (joint with Pat Bayer, Federico Bugni, and Jon James) *Advances in Econometrics,* Vol. 51 (December 2013), 45-96

“Race and College Success: Evidence from Missouri” (joint with Cory Koedel) *AEJ: Applied Economics,* Vol. 6 (July 2014), 20-57

“Affirmative Action and University Fit: Evidence from Proposition 209” (joint with Esteban Aucejo, Patrick Coate, and Joe Hotz) *IZA: Journal of Labor Economics*, Vol. 3, No. 7 (September 2014)

*“A Conversation of the Nature, Effects, and Future of Affirmative Action in Higher Education Admissions” (joint with Thomas Espenshade, Stacy Hawkins, and Richard Sander) *University of Pennsylvania Journal of Constitutional Law*, 17:3 (February 2015), 683-728.

“Exploring the Racial Divide in Education and the Labor Market through Evidence from Interracial Families” (joint with Andrew Beauchamp, Marie Hull, and Seth Sanders) *Journal of Human Capital,* 9:2 (Summer 2015), 198-238.

“Affirmative Action in Undergraduate Education” (joint with Michael Lovenheim and Maria Zhu) *Annual Review of Economics*, Vol. 7 (August 2015), 487-518

“University Differences in the Graduation of Minorities in STEM Fields: Evidence from California” (joint with Esteban Aucejo, and V. Joseph Hotz) *American Economic Review*, Vol. 106, No. 3 (March 2016), 525-562

“Affirmative Action and the Quality-Fit Tradeoff” (joint with Michael Lovenheim) *Journal of Economic Literature,* 54(1) (March 2016), 3-51

“Terms of Endearment: An Equilibrium Model of Sex and Matching” (joint with Andrew Beauchamp and Marjorie McElroy) *Quantitative Economics,* 7(1) (March 2016), 117-156

“The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects” (joint with Joe Altonji and Arnaud Maurel) *Handbook of the Economics of Education Vol. 5, Chapter 7* (May 2016)

“Estimation of Dynamic Discrete Choice Models in Continuous Time with an Application to Retail Competition” (joint with Pat Bayer, Jason Blevins, and Paul Ellickson) *Review of Economic Studies,* 83(3) (July 2016), 889-931

“Productivity Spillovers in Team Production: Evidence from Professional Basketball” (joint with Josh Kinsler and Joe Price) *Journal of Labor Economics,* 35(1) (January 2017), 191-225

Unpublished Papers

“Identifying Dynamic Discrete Choice Models off Short Panels” (joint with Bob Miller) revise and resubmit *Journal of Econometrics*

“College Attrition and the Dynamics of Information Revelation” (joint with Esteban Aucejo, Arnaud Maurel, and Tyler Ransom) revise and resubmit *Journal of Political Economy*

“Conditional Choice Probability Estimation of Continuous Time Job Search Models” (joint with Arnaud Maurel and Ekaterina Roshchina)

“Recovering Ex-Ante Returns and Preferences for Occupations using Subjective Expectations Data” (joint with Joe Hotz, Arnaud Maurel, and Teresa Romano) revise and resubmit *Journal of Political Economy*

“Nonstationary Dynamic Models with Finite Dependence” (joint with Bob Miller) second revise and resubmit *Quantitative Economics*

“Equilibrium Grade Inflation with Implications for Female Interest in STEM Majors” (joint with Tom Ahn, Amy Hopson, and James Thomas)

“The Competitive Effects of Entry: Evidence from Supercenter Expansion” (joint with Paul Ellickson, Carl Mela, and John Singleton)

Awards/Grants

Searle Freedom Trust "Affirmative Action and Mismatch", 2012-2013, $54,141

NSF "Large State Space Issues in Dynamic Models" (with Pat Bayer and Federico Bugni), 2011-2013, $391,114

NSF "CCP Estimation of Dynamic Discrete Choice Models with Unobserved Heterogeneity" (with Paul Ellickson and Robert Miller), 2007-2009, $305,423

NICHD "A Dynamic Model of Teen Sex, Abortion, and Childbearing" (with Ahmed Khwaja) 2004-05. $154,000

Smith Richardson Foundation "Does the River Spill Over? Race and Peer Effects in the College & Beyond" (with Jacob Vigdor) 2003. $50,000

Sloan Dissertation Fellowship 1997-98.

Graduate Student Advising (first time on the market in parentheses)

Chair or co-chair:

Thomas Ahn	2004 (University of Kentucky)
Andrew Hussey	2006 (University of Memphis)
Natalie Goodpaster	2006 (Charles Rivers)
Josh Kinsler	2007 (University of Rochester)
Kata Mihaly	2008 (RAND)
Anil Nathan	2008 (Holy Cross)
Andrew Beauchamp	2009 (Boston College)
Jon James	2011 (Federal Reserve Bank of Cleveland)
Esteban Aucejo	2012 (London School of Economics)
Teresa Romano	2014 (Goucher College)
Marie Hull	2015 (UNC Greensboro)
Tyler Ransom	2015 (Postdoc at Social Science Research Institute, Duke)
Brian Clark	2016 (Federal Trade Commission)
James Thomas	2016 (Postdoc at Yale)
Xiaomin Fu	2017 (Amazon)
John Singleton	2017 (University of Rochester)

Committee Member:

Thomas Anderson	2001 (Bureau of Economic Analysis)
Bethany Peters	2002 (Rhodes)
Justin Trogdon	2004 (University of Adelaide)
Bentley Coffey	2004 (Clemson University)
Derek Brown	2004 (Research Triangle Institute)
Lijing Ouyang	2005 (Postdoc at Centers for Disease Control and Prevention)
Omari Swinton	2007 (Howard)
Kelly Bishop	2008 (Olin School of Business)
Alvin Murphy	2008 (Olin School of Business)
Nicole Coomer[†]	2008 (Workers Compensation Research Institute)
Yang Wang	2009 (Lafayette College)

Aurel Hizmo	2011 (NYU Stern)
Ed Kung	2012 (UCLA)
Kyle Mangum	2012 (Georgia State)
Dan LaFave	2012 (Colby College)
Kristen Johnson	2012 (Research Manager, Harvard Business School)
Songman Kang	2012 (Postdoc at Sanford School)
Jason Roos*	2012 (Rotterdam School of Management)
Hyunseob Kim*	2012 (Cornell Business School)
Patrick Coate	2013 (Postdoc at University of Michigan)
Mike Dalton	2013 (Bureau of Labor Statistics)
Peter Landry	2013 (Postdoc at CalTech)
Kalina Staub	2013 (Lecturer at University of Toronto)
Vladislav Sanchev	2013 (Postdoc at Duke)
Gabriela Farfan	2014 (World Bank)
Chung-Ying Lee	2014 (National Taiwan University)
Lala Ma	2014 (Kentucky)
Deborah Rho	2014 (University of St. Thomas)
Yair Taylor	2014 (Department of Justice)
Gabriela Farfan	2014 (World Bank)
Weiwei Hu	2015 (Hong Kong University of Science and Technology, visiting professor)
Brett Matsumoto**	2015 (Bureau of Labor Statistics)
Joe Mazur	2015 (Purdue)
Jared Ashworth	2015 (Pepperdine)
Ekaterina Roshchina	2016 (Postdoc at University of Washington)
Matt Forsstrom**	2017 (Wheaton College)
Alex Robinson	2017 (Analysis Group)
Ying Shi‡	2017 (Postdoc at Stanford Ed)

(*Fuqua Business student, **UNC student, †NC State, ‡Sanford Public Policy)

Service

Executive committee for the department (1999, 2006-2009), Micro qualifying committee (2000, 2005), Graduate admissions committee (2004, 2006), Chair of faculty computing committee (2004-2006), Micro recruiting committee (2005), Undergraduate reform committee (2005), SSRI Faculty Fellows (2006-2007), Executive Committee of the Graduate School (2006-2007), Director of Graduate Studies (2006-2009), Chair of recruiting committee (2006, 2010), Local Organizing Committee for the North American Meetings of the Econometric Society (2007), Academic Standards committee (2009), Graduate admissions director (2011-2013), Dean of graduate school search committee (2012), Organizer for Cowles conference on Structural Microeconomics (2013), Program Committee for World Congress of the Econometric Society (2015), Program Committee for North American Summer Meetings (2016), Program Committee for International Association for Applied Econometrics (2016, 2017), Senior Recruiting (2016), Program Committee for Society of Labor Economists (2017)

Editorial Responsibilities

Co-Editor, *Quantitative Economics,* (July 2016-present)
Foreign Editor, *Review of Economic Studies* (October 2011-present)
Associate Editor, *Journal of Applied Econometrics*, (January 2007-present)
Associate Editor, *AEJ: Applied Economics,* (May 2009-May 2012)
Editor, *Journal of Labor Economics,* (July 2008-July 2013)
Co-Editor, *Economic Inquiry,* (December 2007-January 2011)

Presentations (since 2010)

2017: (scheduled) Wisconsin, Toronto Education Conference, Central European University. Rees lecture at Society of Labor Economists Conference

2016: Wisconsin, Penn State Economics of Education Conference, BGSE Summer Form Workshop-Structural Micro, keynote speaker for the International Association for Applied Econometrics, Banff Empirical Microeconomics Workshop, NBER Education, Purdue

2015: Minnesota, Brown, Chicago, University of British Columbia, IZA, Mannheim, UCL, London School of Economics, keynote speaker for International Conference of Applied Economics of Education, Carnegie Mellon, Georgetown, Columbia, Universitat Autònoma de Barcelona

2014: Penn Law Symposium on Educational Equality, Austin Institute, Tulane, Michigan Journal of Law Reform Symposium on Affirmative Action, Inter-American Development Bank, Johns Hopkins, AERA Annual Meeting, Tennessee, Chicago Booth, Cowles Conference, University of Pennsylvania, Penn State/Cornell Econometrics Conference, keynote speaker International Conference on "The Economics of Study Choice", HCEO Conference on Identity and Inequality, Federal Reserve Bank of New York, Arizona State

2013: Colorado, UNLV, Sciences Po, Toulouse, Chicago, NBER Education, Iowa State, Stanford, Washington University, Yale

2012: Stanford Ed, Conference for John Kennan, Cowles Conference, CEME Conference on the Econometrics of Dynamic Games, Brookings Conference on Mismatch in Higher Education, NYU, London School of Economics

2011: Princeton, UNC, UNC-Greensboro, BYU, Wisconsin, Johns Hopkins, Yale, University of Nevada-Reno, UC Davis, Harvard, Cornell, Institute for Research on Poverty

2010: UC Santa Barbara, UCLA, Virginia, Paris School of Economics, Harris School, Washington University, Pittsburgh, Michigan, Higher Education Conference at Western Ontario

Appendix C

Appendix C: List of Documents Relied Upon In Forming Opinions

In forming my opinions, I relied upon the following documents, as well as all documents cited in my report.

<u>Documents & Files Produced by UNC</u>

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Depositions (w/ Exhibits)

Jennifer Kretchmar
Stephen Farmer
Jared Rosenberg
Barbara Polk
Ni-Eric Perkins

Third-Party Files

All NCPDI/NCERDC data produced to SFFA

Appendix D

1 Appendix D

1.1 Modeling binary outcomes

I model binary outcomes (e.g. admission/rejection) by making use of a latent index π_i, where i indexes individuals and where

$$\pi_i = X_i\gamma + \varepsilon_i \tag{1}$$

The university accepts individual i if $\pi_i > 0$. In the above equation, X_i represents attributes about candidate i that I observe in the data. One of the tasks of the econometrician is to estimate γ which provides a relationship between the observed characteristics and admissions. There are many factors however that influence the admissions decision that are not observed by the econometrician. ε_i represents these unobserved attributes. If I make an assumption about how the error term ε_i is distributed, I can construct for each candidate his or her probability of admission. A standard assumption is that the unobservables follow a logistic distribution and are independent from the observed characteristics. In this case, the probability of admission is given by:

$$\Pr(Y_i = 1) = \frac{\exp(X_i\gamma)}{\exp(X_i\gamma) + 1} \tag{2}$$

where $Y_i = 1$ if the individual was admitted and 0 otherwise. Specifying the probabilities in this way results in a *logit model*. The parameters, γ, are chosen to best match the patterns of admission seen in the data. Embedded in X_i are indicator variables for the applicant's race/ethnicity. To the extent that certain races/ethnicities receive preferences in admissions after taking into account differences in the other characteristics in X_i (e.g. test scores, UNC ratings, etc.) this will be reflected by positive estimates on the parameters associated with these race/ethnicity indicator variables.

To the extent that there are unobserved characteristics that are i) informative to the admissions decision and ii) are correlated with race/ethnicity then the estimate of the relationship between race/ethnicity and admissions will in part be due to this correlation. The UNC database is unusually rich in its availability of characteristics that may influence the admissions decisions. Such richness partially mitigates the concern that race/ethnicity is picking up something else as we are effectively accounting for much of the 'something else'. But nonetheless there is always a concern that there may be some other measure out there that would explain why racial/ethnic differences are present. This concern becomes mitigated as more controls are added and, as more controls are added, the researcher becomes informed about how the estimates would change if further (though unavailable) controls were added. For example, if adding controls leads to the estimated coefficient on a particular group to become more and more positive then we would expect that pattern to continue with further controls.

The estimated parameters make it possible to calculate how an applicant's probability of admission would change had they been treated like a member of an alternative race/ethnicity. For example, suppose based on the observable characteristics of the applicant (the X's) and applicant would have a 25% chance of admission. This translates into an index value of $\ln(.25/.75)$. In order to evaluate how the applicant's chances of admission would change as a member of an alternative race/ethnicity, I add to this index value the parameter

associated with the alternative race/ethnicity to the index and subtract the parameter associated with the applicant's actual race/ethnicity. This yields a new index value, say π^*. The probability of admission given this new index value is then given by $\exp(\pi^*)/(1+\exp(\pi^*))$.

1.2 Modeling ordered outcomes

UNC ratings take on one of a discrete number of values. For example, the program rating takes on the integer values from one to ten. The values are ordered in the sense that a 10 is better than a 9, a 9 is better than an 8, etc. Like in the case of admissions, I define a latent index π_i^R, where i indexes individuals and where

$$\pi_i^R = X_i^R \gamma^R + \varepsilon_i^R \tag{3}$$

where R indexes the rating being considered.

Suppose, such as the case with the personal quality rating, that the rating takes on one of five values: 1, 3, 5, 7, or 10. Then the observed rating, Y_i^R takes on a particular value, say 3, when π is in a certain range. Namely:

$$Y_i^R = \begin{cases} 10 & \text{if } \pi_i^R \geq k_{10} \\ 7 & \text{if } k_{10} > \pi_i^R \geq k_7 \\ 5 & \text{if } k_7 > \pi_i^R \geq k_5 \\ 3 & \text{if } k_5 > \pi_i^R \geq k_3 \\ 1 & \text{if } k_3 > \pi_i^R \geq \end{cases} \tag{4}$$

where $k_{10} > k_7 > k_5 > k_3$ are the thresholds associated with each ranking. Both the index parameters, γ, and the thresholds, the k's, are then estimated. As with the admissions model, a distributional assumption is required on the ε's. I again assume a Type 1 extreme value distribution which leads to an ordered logit model. The probabilities of receiving each of these rankings given X_i is then given by:

$$\begin{aligned}
Pr(Y_i^R = 1) &= \frac{\exp(k_3 - X_i^R\gamma^R)}{1+\exp(k_3 - X_i^R\gamma^R)} \\
Pr(Y_i^R = 3) &= \frac{\exp(k_5 - X_i^R\gamma^R)}{1+\exp(k_5 - X_i^R\gamma^R)} - \frac{\exp(k_3 - X_i^R\gamma^R)}{1+\exp(k_3 - X_i^R\gamma^R)} \\
Pr(Y_i^R = 5) &= \frac{\exp(k_7 - X_i^R\gamma^R)}{1+\exp(k_7 - X_i^R\gamma^R)} - \frac{\exp(k_5 - X_i^R\gamma^R)}{1+\exp(k_5 - X_i^R\gamma^R)} \\
Pr(Y_i^R = 7) &= \frac{\exp(k_{10} - X_i^R\gamma^R)}{1+\exp(k_{10} - X_i^R\gamma^R)} - \frac{\exp(k_7 - X_i^R\gamma^R)}{1+\exp(k_7 - X_i^R\gamma^R)} \\
Pr(Y_i^R = 10) &= 1 - \frac{\exp(k_{10} - X_i^R\gamma^R)}{1+\exp(k_{10} - X_i^R\gamma^R)}
\end{aligned}$$

As with the logit model of admissions, to the extent that certain races/ethnicities receive preferences in the ratings after taking into account differences in the other characteristics in X_i^R (e.g. test scores, UNC's other ratings, etc.) this will be reflected by positive estimates of the parameters associated with these race/ethnicity indicator variables.